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

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ABSTRACT

The development of mechanistic-empirical pavement design has increased demand for measuring performance-related soil properties during earthwork construction. Tools such as the light weight deflectometer (LWD) allow for quantification of the stiffness of subgrade materials during construction. However, a major limitation of the LWD is its inability to provide subgrade stiffness information over the entire project site. The development of continuous compaction control (CCC) has provided the ability to collect near continuous measurements of compaction effort information during the compaction process through the instrumentation of compaction rollers. In this study, LWD and CCC measurements (compactometer value, CMV) were collected during active construction of a roadway. Target modulus values from LWD measurements were determined utilizing AASHTO TP 123-17 to indicate passing and failing LWD tests collected in the field. This study examined general trends between recorded localized CMV measurements and local passing and failing LWD measurements, to assess the utility of CMV as a quality assurance tool for earthwork construction.

INTRODUCTION

Traditionally, the compaction of soils during earthwork construction has benefitted from the use of various approaches to Quality Assurance/Quality Control (QA/QC). One common method that is utilized is "end-product" specifications, which typically mandate measurement of a soil's dry density (or unit weight) and moisture content in the field, with the resulting data being compared against standardized laboratory compaction test results (e.g., Proctor 1933, ASTM D698-12, ASTM D1557-12). Most end product specifications require that minimum target relative compaction requirements for a given project are achieved (e.g., 90% or 95% of maximum dry unit weight and ± 2% of optimum moisture content are commonly specified, as measured using either the Standard or Modified Proctor test). In the highway community, there has recently been a fundamental shift in the way pavement design is performed, following the development of AASHTO's mechanistic-empirical pavement design guide (AASHTO 2008). This approach to pavement design utilizes the principles of engineering mechanics in order to predict pavement responses (e.g. stress, strain, deflection) to simulate the behavior of a pavement system under a given traffic loading condition. Consequently, soil parameters such as resilient modulus (AASHTO T 307-99) are utilized in the design process to predict pavement performance.

Given this change in the way pavement systems are designed, there has been an increased interest in measurement of a soil's mechanical properties (e.g. modulus) in situ during construction. One device that was developed for this purpose is the Light Weight Deflectometer or LWD (ASTM E2583-07). The LWD is comprised of a circular loading plate, typically 15 – 30 cm in diameter, a guide rod, a urethane load damper and a drop mass that typically ranges between 10 – 20 kg depending on the manufacturer (e.g., Mooney and Miller 2009, Meehan et al. 2012, Stamp and Mooney 2013). In order to measure the response from a LWD test, either a geophone or accelerometer is utilized; some manufacturers also utilize a load cell to measure the applied load while other manufacturers assume a constant applied load for a given drop height (Schwartz et al. 2017). Assuming that the soil being tested is linear-elastic, isotropic and homogeneous, the soil modulus that can be extracted from an LWD test is defined as:

$$E_{Field} = \frac{2F_{peak}(1-\upsilon^2)}{Ar_0 w_{peak}} \tag{1}$$

where F_{peak} and w_{peak} are the peak applied force and displacement measured by the LWD, υ is Poisson's ratio, r_0 is the plate radius of the LWD, and A is the assumed contact stress distribution of the LWD, which is a function of soil type and is generally classified as either being an inverse parabolic distribution, a parabolic distribution, or a uniform distribution (Timoshenko and Goodier 1951).

Other innovative approaches to monitoring soil compaction have also been developed, including Continuous Compaction Control (CCC) and Intelligent Compaction (IC), which allow for more continuous monitoring of the compaction process (e.g., Mooney et al. 2010, Meehan and Tehrani 2011). CCC/IC systems are generally comprised of three components installed on a compaction roller: a sensor mounted on the drum (e.g., an accelerometer), a real time kinematic global positioning system (RTK-GPS) that allows for accurate roller position measurements, and an on board computer in the cab of the roller, which provides real-time data and spatial maps of the compaction process (Mooney et al. 2010). The hypothesis of CCC/IC behavior is that the roller drum and the soil being compacted constitute a coupled system, in which changes in the soil's stiffness during compaction result in changes in the vibratory characteristics of the roller drum (Imran et al. 2018). These changes in the vibratory characteristics are realized by monitoring the acceleration signal of the drum and manipulating the signal to provide a roller-determined measurement value (RDMV). One such RDMV is called the Compactometer Value (CMV), which is calculated from the ratio between the amplitudes of the first harmonic of the measured acceleration response signal and the excitation frequency of the roller drum. Early research by Thurner and Sandstrom (1980) indicated that as soil becomes more compacted during the compaction process, the frequency content of the measured acceleration response signal changes, more specifically the amplitude of the first harmonic increases. Consequently, all things being equal, a higher CMV generally corresponds to a stiffer soil that is being compacted. CMV is considered to be an "indicator" value, meaning it is not a direct measurement of the soil's physical or mechanical properties (e.g. density or modulus). Therefore, the use of CMV during earthwork construction requires that traditional in situ testing also be conducted in parallel for QA/QC purposes.

Various researchers (e.g., Rinehart et al. 2012, Meehan et al. 2017, Cai et al. 2017) have made attempts to correlate CCC/IC RDMVs with traditional in situ testing measurements. These researchers have observed highly variable (i.e., "poor" to "good" quality) correlations, with R^2 values generally ranging from 0.3 to 0.8 when utilizing simple linear regression techniques. These early efforts were made in an attempt to determine if RDMVs could be calibrated to actual soil properties (e.g., density or modulus) determined via in situ testing measurements, in order to take full advantage of CCC/IC technologies for earthwork QA/QC purposes. Though early research has indicated that simple correlation analysis is not robust enough to calibrate CCC/IC

RDMVs for earthwork QA/QC purposes, other methods still need to be explored. Recently, a proposed procedure has been developed to determine a “target” modulus value for LWD testing in the field. The proposed procedure (AASHTO TP123-17) is an extension of traditional laboratory Proctor analysis, where for each Proctor point a series of LWD tests are conducted on the proctor mold at various drop heights. For the sake of brevity, interested readers are referred to Chapter 5 of Schwartz et al. (2017) for details on how this laboratory procedure is conducted and then utilized to develop a target modulus value.

For this study, LWD and CMV measurements were collected during active earthwork construction, and parallel laboratory tests were conducted utilizing AASHTO TP 123-17 to determine a target modulus value for the LWD tests. The goal of this study was to assess the general trends between CMV readings that were associated with “failing” and “passing” LWD tests in the field to assess the applicability of utilizing CMV as a quality assurance tool for earthwork construction. A machine learning technique, Support Vector Machine (SVM), was utilized to develop a decision-boundary between passing and failing CMV measurements (e.g. CMV values at specific LWD test locations) with respect to moisture content. The models developed using SVM were able to identify regions of CMV readings with respect to moisture content that were considered passing or failing with at least 90% accuracy.

PROJECT DESCRIPTION

CMV and LWD Data Collection during Active Construction

CMV readings and LWD measurements were collected during active construction of US 301, Section 3 located in Middletown, DE. CMV readings were collected utilizing a Caterpillar CS56B smooth drum compaction roller that was instrumented with a CCS900 Continuous Compaction Control retrofit kit. LWD measurements were collected utilizing a 30 cm diameter Zorn Light Weight Deflectometer with a 10 kg drop weight following the procedure outlined in ASTM E2583-07. This LWD is not instrumented with a load cell to measure peak force applied during testing; however, the manufacturer indicates that the applied force for this LWD is calibrated to 7.07 kN. For this study, CMV readings, LWD measurements, and representative moisture content samples were collected during the active construction of four embankment sections. During the construction of these embankment sections the compaction roller utilized in this study was operated at a “low” vibratory amplitude setting (e.g., 0.98 mm), with a fixed vibratory frequency of 31.9 Hz. A total of 120 LWD tests were conducted along the four embankments; due to the geometry of each section tested and to avoid conflicts with the contractor there was a variation in the number of tests conducted along each embankment. The numbers of tests conducted along each embankment were 49, 26, 30, and 15, respectfully. At each LWD test location along all embankment sections, physical soil samples were collected for moisture content determination utilizing ASTM D2216-10. It should be noted that the soil utilized as subgrade material for all embankment sections was retrieved from an onsite borrow and was generally classified as either a silty sand (SM) or poorly graded silty sand (SP-SM), as indicated by Baker and Meehan (2019). Given that the CMV measurements collected were more continuous in nature compared to the LWD tests collected, it is common practice to utilize geospatial interpolation techniques to estimate RDMVs at location specific in situ testing locations (e.g., Meehan et al. 2017). For this study a simple inverse distance weighting approach was utilized, with a p value of 1 and a neighborhood size of 1 m around each LWD testing location. Other, more sophisticated interpolation methods were not examined, as the results from

Meehan et al. (2017) indicated that estimated RDMVs are not significantly influenced by the type of interpolation technique that is utilized.

Laboratory Procedure to Determine LWD Target Modulus

Representative bulk samples were collected to perform laboratory tests to determine a target modulus. A target modulus value for a given LWD measurement taken in the field is determined using the following equation, as outlined in AASHTO TP 123-17:

$$E_{Target} = a_0 + a_1 MC_{Field}^{\ 2} + a_2 MC_{Field} + a_3 P_{Field}^{\ 2} + a_4 P_{Field} \tag{2}$$

$$P_{Field} = \frac{F_{Field}}{\pi\left(\frac{D_{Field}}{2}\right)^2} \tag{3}$$

where E_{Target} is the target modulus for a given LWD test conducted in the field, MC_{Field} is the moisture content measured in the field for a given LWD test, P_{Field} is the applied pressure from the LWD, F_{Field} is the applied force from the LWD, D_{Field} is the diameter of the LWD, and a_0 through a_4 are multivariate regression coefficients. In order to determine the a_0 through a_4 coefficients, a multivariate regression analysis should be performed utilizing the following equation in conjunction with a series of laboratory LWD tests that need to be conducted:

$$E_{Soil} = a_0 + a_1 MC_{mold}^{\ 2} + a_2 MC_{Mold} + a_3 P_{Mold}^{\ 2} + a_4 P_{Mold} \tag{4}$$

where E_{Soil} is the elastic soil modulus measured from the laboratory LWD, MC_{mold} is the laboratory determined moisture content, and P_{mold} is the applied pressure from the laboratory LWD. Laboratory LWD tests were conducted utilizing a 15 cm plate diameter LWD with a 5 kg drop mass manufactured by Zorn Instruments. For this study, “standard” compaction energy was utilized (e.g. ASTM D698-12, AASHTO T99-18) as this approach was used elsewhere by DelDOT personnel to conduct their QA/QC testing during the construction of US 301, Section 3 (DelDOT 2016). Using the laboratory determined regression coefficients a_0 through a_4, measuring the deflection from LWD testing, and collecting associated moisture content samples in the field, both E_{Field} (Eq. 1) and E_{Target} (Eq. 2) can be calculated. In order for a given LWD test conducted in the field to “pass” the following equation is utilized:

$$E_{Field} \geq E_{Target} \tag{5}$$

If this equation is not satisfied then the associated LWD test conducted in the field has “failed”, otherwise the LWD test has “passed”.

Support Vector Machine Decision Boundary

Support Vector Machine (SVM) is a type of supervised machine learning technique that is utilized to determine an optimum boundary that separates two or more categories associated with a specific data set. The general theory behind SVM is to construct a separating hyperplane (e.g. decision boundary) such that the distance between different categories of data within the same data set are maximum, e.g. the largest boundary between different categories is developed. In cases were the data is not linearly separable, SVM takes advantage of kernel functions to map the data into a higher dimensional/feature space that enables the data to be linearly separable (Goh and Goh 2007). SVM has been utilized for geotechnical applications such as liquefaction detection and other applications (Goh and Goh 2007). For this study, the data set of LWD and associated CMV values could be classified as either “passing” or “failing” based on the procedure of the previous section; consequently, SVM was utilized to develop a boundary surface between passing and failing CMV tests with respect to moisture content. For this study, both linear and quadratic SVMs were utilized to create the boundary surface between passing and failing points.

RESULTS

For the LWD measurements collected in the field, average deflection values ranged from 0.33 mm to 6.66 mm with a global average deflection of 0.97 mm. Utilizing Equation 1, this yielded elastic soil modulus values from 4.83 MPa to 97.78 MPa with an average soil modulus of 47.27 MPa. Associated averaged CMV readings ranged from 5.9 to 70.6 with a global average CMV reading of 33.82. Associated moisture content samples ranged from 4.6% to 19.6% with a global average moisture content of 10.7%. It should be noted that when calculating the associated CMV readings at location specific LWD test locations, there were 10 locations where interpolated CMV readings could not be determined, as CMV readings were not within the 1 m neighborhood search radius at these locations. Therefore, only 110 samples were utilized to develop the SVM boundary surfaces.

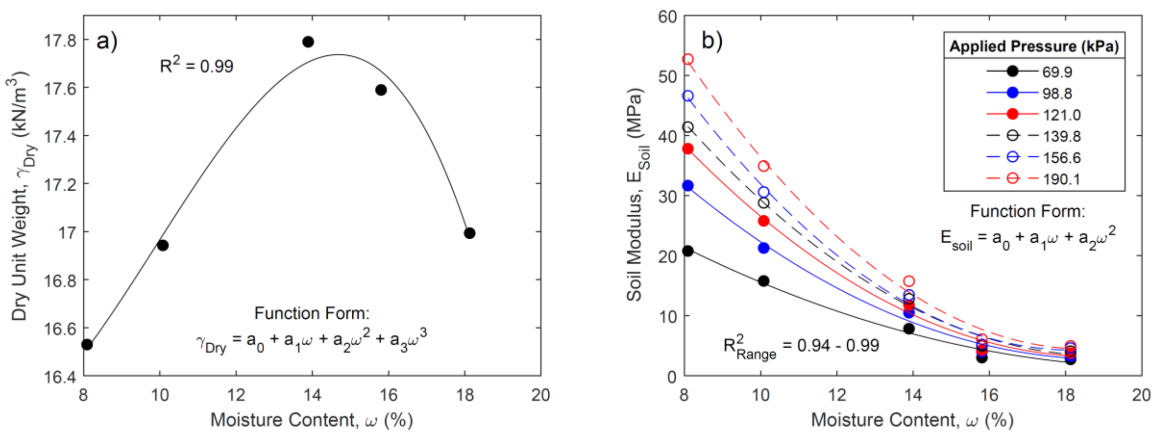

Figure 1. Laboratory results following AASHTO TP-123: a) Dry unit weight variation with moisture content, and b) Soil modulus variation with moisture content.

Figure 1 presents the results from the laboratory determination of the target elastic soil modulus. From Figure 1a, the results indicated that the maximum dry unit weight calculated was 17.73 kN/m^3 with an optimum moisture content of 14.7%. Laboratory determined elastic soil modulus values ranged from 2.73 MPa to 52.7 MPa for the range of applied pressures utilized; this was done by varying the drop height of the laboratory LWD mass for each proctor point that was created. As one would expect, the more pressure that was applied by the laboratory LWD the stiffer the response of the soil, which yielded a higher calculated elastic soil modulus. This phenomena was more apparent for moisture content values that were less than optimum. For moisture content values at or above optimum, this phenomena diminished. This is apparent in Figure 1b, where the trend lines for each associated applied pressure tend to merge together as the soil's moisture content increases. The results presented in Figure 1 indicate that the influence of moisture content on the two parameters, unit weight and elastic soil modulus, differ. As with most proctor analyses, unit weight tends to behave like a bell curve, with a maximum dry unit weight increasing with moisture content until it achieves a maximum value at the soil's optimum moisture content. Beyond the optimum moisture content, the dry unit weight decreases with increasing moisture content. Elastic soil modulus, on the other hand, decreases monotonically with increases in moisture content. Equation 4 was then utilized to determine the multivariate regression coefficients a_0 through a_4. It should be noted that the applied pressures were normalized to atmospheric pressure (101.3 kPa) prior to performing the multivariate regression analysis. The following values were determined from the analysis (Table 1):

Table 1. Coefficient Values from Multivariate Regression Analysis

a_0	a_1	a_2	a_3	a_4
93.08	0.31	-11.5	-3.09	18.66
		R^2 = 0.93		

The values from Table 1 along with Equation 2 were utilized to determine the associated target modulus values for each LWD test conducted during the construction of US 301 Section 3. When utilizing this approach, 18 out of the 110 LWD measurements used to develop the boundary surface (e.g., 16%) did not achieve their target value based on the procedure outlined above. It should be noted that the LWD measurements collected during this study were collected at the end of the compaction process along each embankment. Given that this study took place during active construction, the authors did not interfere with the contractor's work and did not obtain LWD measurements during the initial and intermediate stages of the compaction process. Therefore, it is reasonable that only 16% of the LWD measurements did not meet their target value.

In order to assess the applicability of CMV as a QA/QC procedure for earthwork construction, SVM decision boundaries was developed utilizing the *fitcsvm* function in MATLAB. 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. Figure 2 presents the results of the two SVM boundary surfaces developed. 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. In summary, the linear model misclassified 5 passing points and 2 failing points, and the quartic model misclassified 6 passing points and 2 failing points. The points circled in Figure 2 are known as support vectors. Support vectors are points from both classes (e.g. passing and failing points) that are clustered around the decision boundary. SVM utilizes these points to optimize the decision boundary so that the margin between passing and failing points is maximized (Goh and Goh 2007). When comparing two kernel functions the use of a linear kernel function provides a more conservative decision boundary, as a larger failed region is developed compared to the quadratic kernel function. In a general sense, both decision boundaries developed would generally classify a failed compaction point as a point with a CMV value of 30 or less and an associated moisture content ranging between 4-10%.

Overall, the use of SVM as a means for integrating CMV measurements into a passing and failing point framework with respect to target modulus and moisture content values shows promise for incorporating CMV and other CCC technologies into QA/QC approaches for earthwork construction. In particular, the development of a decision boundary indicating passing and failing regions can provide both contractors and state agencies a practical application that uses CCC technology as an earthwork QA/QC tool. However, the current use of SVM in this fashion does have some drawbacks, namely the limited number of failing points that were used to develop the decision boundaries. 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 in order to better understand the behavior of these decision boundaries, additional data is required. More specifically, this additional data should include more failing points in order to better characterize these decision boundaries for a given soil type. The addition of more failing points will also allow sensitivity analyses to be conducted including techniques such as cross validation and separating the data set into training and validation data sets. The use of these techniques will be helpful in determining the robustness of SVM models in this context.

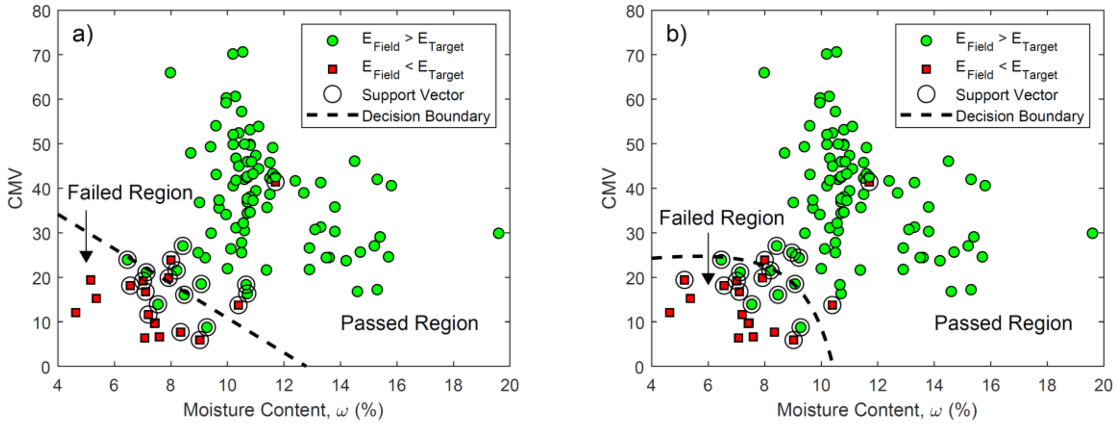

Figure 2. Passing and failing regions developed utilizing Support Vector Machine: a) Linear kernel function, and b) Quadratic kernel function.

CONCLUSIONS

Earthwork QA/QC is experiencing a fundamental shift towards measurement of a soil's mechanical properties instead of physical properties (e.g., modulus vs density), driven by the shift to mechanistic-empirical pavement design. This shift has enhanced the utilization of devices such as the Light Weight Deflectometer (LWD), which allow a soil's elastic modulus to be measured in situ. Other technologies such as Continuous Compaction Control and Intelligent Compaction (CCC/IC) have also been developed in order to more continuously assess the compaction process by monitoring the vibratory behavior of the compaction drum and providing indicator values (e.g. Roller Determined Measurement Values) in real-time. LWD testing, like other in situ testing devices, can only be conducted at discrete locations and cannot provide continuous coverage of the evaluation area. CCC/IC technologies provide near 100% coverage of the evaluation area, but only provide indicator values that are not a true measure of the soil's mechanical properties necessary for design of overlying pavement systems. There is consequently a benefit to combining these two approaches into a synergistic framework.

In the current study, target elastic soil modulus values for LWD tests conducting during active construction were determined by following the procedure outlined in AASHTO TP123-17. During the active construction of multiple embankments, CMV readings were collected utilizing a compaction roller with CCC technology, and localized LWD tests were also conducted along with soil sampling for later determination of moisture contents. CMV readings were interpolated to find corresponding values at the localized LWD test locations, in order to develop a data set consisting of localized CMV readings, moisture content, and binary values of 1s and 0s indicating "passing" and "failing" LWD tests conducted in the field, as determined by the AASHTO TP123-17 procedure. Two Support Vector Machine (SVM) models were then developed using this data, to determine passing and failing boundaries with respect to localized CMV measurements and moisture content.

The two SVM models developed had a 91% 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 that allows for relatively continuous assessment during the earthwork construction process. Though promising, the current data set is limited to a small percentage of failing points (e.g. 16%), as the data was collected at the end of the compaction process for lifts that were generally well-compacted. More data in needed in future studies of this type, especially the collection of more failing points, in order to validate these initial findings and to better understand the general trends that are present when using machine learning techniques (e.g., 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 and R. David Charles) for facilitating access to the project site during the duration of this study.

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