A Comparison of Simultaneously Recorded Machine Drive Power and Compactometer Measurements

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Abstract: Continuous compaction control (CCC) systems are data acquisition systems installed on compaction equipment that continuously collect real-time information about the operation and performance of the compactor. An experimental research study was conducted to examine the type of data that is recorded by CCC equipment during road sub-base compaction of "select fill" granular materials using a smooth-drum vibratory roller. A prototype roller was utilized that allowed for simultaneous real-time machine drive power and compactometer measurements, which permitted independent and simultaneous evaluation of the degree of compaction of the soil. The behavior of the recorded machine drive power and compactometer values for different lifts and with increasing compactive effort for a single lift is presented and discussed. The statistical nature of the recorded CCC data sets is explored in detail, with a focus on distribution fitting assessment techniques that are applicable for CCC data. Comparisons are also made between the simultaneously recorded machine drive power and compactometer measurements. The results and associated discussion that are presented are useful for understanding the variable nature of CCC data sets, and the observations that are made have practical implications for the creation of CCC construction specifications that are to be used to control the compaction process.

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1 Introduction

Continuous compaction control (CCC) systems are data acquisition systems installed on compaction equipment that continuously collect real-time information about the operation and performance of the compactor (Thurner and Sandström 1980; Adam 1997; Adam and Brandl 2003). For vibratory compactors, the data that is often collected includes the vibratory frequency, the amplitude of the roller drum, and the speed of the roller (Adam 1997). For machine drive power (MDP) based systems, the gross power that is applied by the compactor is typically recorded, in addition to other properties such as roller speed, roller acceleration, and the slope angle (White et al. 2005). Intelligent compaction (IC) is a mechanism whereby CCC data is interpreted and used in real-time to adjust the operation of the compactor in an attempt to optimize the compaction process and to achieve more uniform soil compaction (Adam and Brandl 2003; Anderegg et al. 2006).

Since the introduction of CCC and IC compaction equipment, several field studies have been conducted to evaluate the effectiveness and productivity of these new technologies (e.g., Thurner and Sandström 1980; Adam 1997; Adam and Brandl 2003; White et al. 2005; Peterson et al. 2006). In the early stages of development of these technologies, it was discovered that vibratory-based CCC and IC systems held significant promise for compaction of coarse-grained materials (e.g., sand and gravel, Adam 1997; Adam and Brandl 2003). More recently, it has been noted that these vibratory-based CCC techniques are not as effective when dealing with finer-grained soils (e.g., silt and clay) that are commonly used in construction in many regions throughout the United States (e.g., White et al. 2005). To overcome this limitation, compaction

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equipment manufacturers have begun exploring the use of MDP technologies for real-time compaction control of fine-grained soils. Current MDP technology originates from the theory of terrain-vehicle systems (Bekker 1969), and utilizes gross engine power to determine the degree of compaction. This technology is advantageous because it does not rely on a vibratory mechanism for evaluation of compaction performance, which is more consistent with the way that fine-grained soils are commonly compacted (e.g., tamping compactors or sheep-footed compactors). Given the potential promise of this new technology, it is possible that all future IC/CCC equipment will contain both MDP-based and vibratory-based measurement systems, which will allow for more effective compaction control in both granular and fine-grained materials.

To evaluate the performance of equipment that utilizes both MDP-based and vibratory-based measurements for quality control of road sub-base compaction, an experimental study was conducted in the State of Delaware in the summer of 2008. Under carefully controlled conditions at a state borrow area site, a road sub-base test pad was constructed and compacted using a prototype Caterpillar CS56 vibratory smooth drum roller. This prototype roller was specially modified to allow for real-time machine drive power (MDP) and compactometer value (CMV) measurements, which permitted independent and simultaneous evaluation of the degree of compaction of the soil (more detail about how these types of measurements are made is provided in a later section). The soils utilized during this study were granular in nature, are considered to be "Select Fill" materials by the Delaware Department of Transportation (DelDOT) (DelDOT 2001 - Section 301), and have a USCS classification of either poorly graded sand with silt (SP-SM) or silty sand (SM) (ASTM D2487-06 2007).

This paper presents the measured MDP and CMV results from the field study that was performed. The behavior of the recorded values for different lifts and with increasing compactive effort for a single lift is presented and discussed. The statistical nature of the recorded CCC data sets is explored in detail, with a focus on distribution fitting assessment techniques that are applicable for CCC data. Direct comparisons are made between the simultaneously recorded MDP and CMV measurements. The measured data, analysis approach, and associated discussion that are presented are useful for understanding the variable nature of CCC data sets, and the observations that are made have practical implications for the creation of CCC construction specifications that can be used to control the compaction process.

2 Project Description

The CCC field study described in this paper was performed at Burrice Borrow Pit in Odessa, DE (United States) in July of 2008. A 61 m long by 6 m wide (200 ft by 20 ft) embankment was built out of poorly graded sand with silt (SP-SM) and silty sand (SM). The former classification was predominant, as indicated by 36 out of the 53 soil classification tests that were performed (ASTM D2487-06 2007); however, in general, the material was quite uniform, and only had two classifications because it tended to fall at the boundary between two soil types (Fig. 1). This soil is a commonly used borrow material for DelDOT, and it conforms to state "Select Fill" borrow specifications: Class G, Grades V and VI (DelDOT 2001 - Section 301, Fig. 1). The embankment was constructed to an approximate total final height of 0.9 m (3.0 ft), by compacting five 20.3 cm (8 in.) loose-lift layers, in accordance with Delaware general specifications for road sub-base construction (DelDOT 2001).

To construct each lift, a Caterpillar 980H bucket loader was used to place fill for spreading by an on-site bulldozer. A Caterpillar D6K dozer was then utilized for spreading the material to an approximate loose-lift thickness of 20.3 cm (8 in). The D6K dozer was equipped with a global positioning system (GPS), which proved beneficial for establishing a relatively uniform and consistent loose-lift thickness. Two methods were used to verify the expected loose-lift thickness of each lift; during fill placement the dozer operator checked it via the GPS mounted on the dozer blade, and after lift completion the thickness was confirmed by spot-checking elevations throughout the test pad area using a GPS rover unit. After spreading each lift, a water truck was driven through the test area as needed to adjust the moisture content of the fill material to achieve optimum compaction.

Upon completion of loose-lift soil placement and moisture conditioning, each soil lift was compacted using a Caterpillar CS56 vibratory smooth drum roller. This prototype machine had been specially modified by Caterpillar research engineers to measure both MDP and CMV values simultaneously. It also utilized an on-board GPS to accurately establish the location of the compactor in real-time, as it made in situ measurements. The roller drum was 2.1 m (7 ft) wide, and had an operating weight of 11,414 kg (25,164 lb). Compaction was performed using both low and high-amplitude vibration (0.85 and 1.87 mm, 0.033 and 0.074 in.), at a vibratory frequency of about 31.9 Hz (1,914 vibrations per minute). During compaction, the roller speed was kept relatively constant, at around 3.25 km/h. Typically, to speed up the compaction process, high-amplitude compaction was performed on the loose materials in the first pass for each layer, and the following passes were performed using low-amplitude compaction. This approach was used to prevent overcompaction and to generate CMV values that were more representative of the layer that was being compacted (this was necessary because higher amplitude compaction was assumed to cause the measured CMV values to be more affected by the stiffness of underlying soil layers). In addition, at the outset of this research study, it was assumed that using high-amplitude compaction for all passes would increase the probability of entering into a "double jump" mode of vibration, which was not desirable (Anderegg and Kaufmann 2004). MDP and CMV values were collected approximately every 15 cm (6 in.) along the length of the test sections.

Using the modified Caterpillar CS56 compactor, each

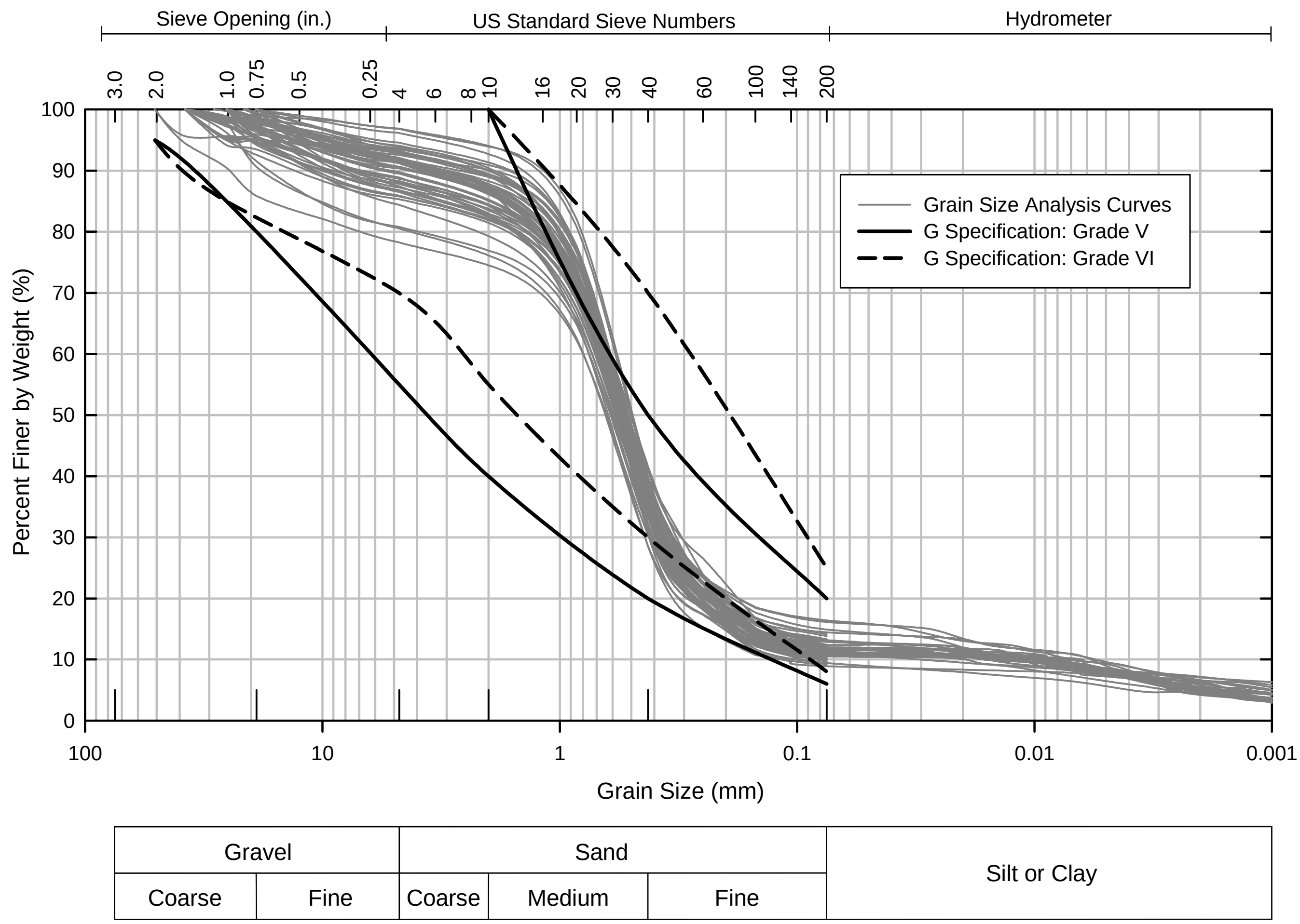

Fig. 1: Gradation results for field samples taken from various locations during embankment construction.

lift was compacted in a series of passes using three side-by-side lanes (the roller width was 2.1 m (7 ft), the test pad width was 6 m (20 ft), which left approximately 15 cm (6 in) of overlap at the edges of each compacted soil "lane"). For each lift, between six and nine compactor passes were performed to achieve the desired level of compaction (target dry unit weights $\geq$ 95 % of the Standard Proctor maximum dry unit weight). During compaction, a computer screen in the cab displayed real-time MDP and CMV measurements to the roller operator using a color coded map. Once relatively little change in MDP value was observed by the operator, compaction for a given lift was stopped. The number of compactor passes that were performed to achieve compaction in this study are consistent with the level of compactive effort that is typically required to meet the current DelDOT dry-density specifications, based on technician experience with this borrow soil at other field construction projects (DelDOT representative, personal communication); this observation was later verified by examining the results from a series of nuclear density gauge tests and 1-pt Standard Proctor tests.

For this borrow material, DelDOT uses a 1-pt Standard Proctor test approach in conjunction with an established "family of compaction curves" to establish the maximum dry unit weight and optimum moisture content at each compaction control in situ test location (DelDOT 2001; AASHTO T 99-01 2001; AASHTO T 272-04 2004). During this field study, using this approach at 49 in situ test locations yielded a mean maximum dry unit weight of 18.8 kN/m^3 (with a standard deviation of 0.39 kN/m^3) and a mean optimum moisture content of 11.7 % (with a standard deviation of 0.78 %). In situ moisture content values measured using a nuclear density gauge (ASTM D3017-05 2007) ranged between 7.2 and 11.8 %; the majority of the measured field moisture content values were on the dry side of optimum.

A more detailed discussion about the observed variability in the in situ unit weight, moisture content, and soil grain size characteristics during embankment construction is provided in Tehrani (2009). Interested readers are referred to this publication for more details, as a large amount of supplemental data of potential interest is presented there. As the focus of the current manuscript is on performing a comparison of simultaneously recorded CCC values with each other, not with other types of soil measurements or characteristics (e.g., unit weight, moisture content, etc.), this data is not presented herein.

3 Mathematical Indicators of Soil Compaction Used in This Study

According to Thurner and Sandström (1980, 2000) for vibratory CCC systems the CMV is calculated by dividing the amplitude of the first harmonic of the measured response acceleration at the compactor drum by the amplitude of the exciting frequency of compaction (Eq 1, Thurner and Sandström (1980, 2000). As the soil becomes stiffer, the amplitude of the first harmonic increases, causing a corresponding increase in CMV

$$\mathrm{CMV} = C \cdot \frac{\hat{a}(2w_0)}{\hat{a}(w_0)} \tag{1}$$

where:

$\hat{a}(2w_0)$ = amplitude of the first harmonic of the acceleration response signal,

$\hat{a}(w_0)$ = amplitude of the exciting frequency and

C = constant value chosen to empirically scale the output CMV values to an easier-to-interpret range.

Using $C = 300$ has become a commonly accepted and standardized approach for calculating CMV values from measured vibratory roller data (Sandström and Pettersson 2004).

MDP is a mathematically calculated value of power that isolates the internal resistance to compactor drum rolling that is provided by the soil (Eq 2, White et al. 2006)

$$\mathrm{MDP} = P_n = P_g - WV\left(\sin\alpha + \frac{a}{g}\right) - (mV + b) \tag{2}$$

where:

P_n = net power required to propel the compactor through an uncompacted layer of fill,

P_g = gross power needed to move the machine,

W = roller weight,

V = roller velocity,

a = acceleration of the machine,

g = acceleration of gravity,

α = slope angle, and

m and b = machine internal loss coefficients specific to a particular machine.

For a soil that is being compacted by drum rolling, as the degree of compaction increases, the underlying soil becomes denser, the energy consumed to propel the roller (the gross power needed) decreases, and the MDP decreases (White et al. 2006). The prototype CS56 roller that was used in this study recorded roller-specific MDP values, which are commonly referred to as MDP* values (White et al. 2009). In order to compare the MDP values measured in this study with data collected by other researchers, it is useful to calculate standardized MDP values that are not machine-specific (commonly referred to as MDP values, as defined in Eq 2). For the roller used in this study, these values were calculated from the machine output data (MDP*) using Eq 3, which is determined from a machine-specific calibration relationship (Tehrani and Meehan 2009).

$$\mathrm{MDP} = \left(-\frac{54.23\ \mathrm{kW}}{150}\right)(\mathrm{MDP}^* - 150) \tag{3}$$

By combining the calculated MDP and CMV values with their corresponding point-specific coordinates determined using the on-board GPS system, a spatial map of CCC measurements can be built, and these roller-measured values can be used to provide quality control over the compaction process.

4 CCC Roller Measurements

Figure 2 presents recorded MDP and CMV data versus distance for different compaction passes on Lift 5 of the embankment that was constructed. The data shown corresponds to a single transect (a single roller lane) along the centerline of the embankment. As shown in this figure, the spatial distribution of the recorded MDP and CMV values over the compacted area is quite uneven and is highly variable from point-to-point. The heavier lines shown in Fig. 2 reflect the average of the measured data along each transect. The change in these average values from Pass 2 to Pass 7, with increasing compactive effort, is quite apparent. However, the point-to-point variability in recorded MDP and CMV values is quite large in all cases, which makes point-specific comparisons from pass-to-pass (or with point-specific in situ test results) quite difficult.

The "noisy" MDP and CMV behavior shown in Fig. 2 is consistent with the type of CCC data that has been reported by other researchers for various types of soils (e.g., White and Thompson 2008; White et al. 2008). There are a number of possible reasons for this noisy behavior: In general, the soil under compaction is not homogeneous and the grain size, grain shape, and in situ void ratio of the compacted material can vary significantly along the roller path. Soil-water characteristics and distribution of soil moisture during the process of field compaction can also play a contributing role. As noted in Tehrani (2009), the moisture content of the soil was not constant throughout the compacted area, and this variability can have an influence on the mechanical properties of the compacted soil. Other unknown measurement factors also likely have an effect, including electrical noise in the data acquisition system and a variable response of the monitoring instruments to the ground conditions. Despite the irregular shape of the CCC data over the study area, a clear trend in the average of the measured values shows that with increasing compactive effort, the overall CMV values increase and MDP measurements decrease. This behavior is consistent with the nature of these CCC values.

Another useful approach for visualizing the roller-measured CCC values is to present the measured data for each lift and pass in the form of histograms, and to calculate the associated mean, standard deviation, and coefficient of variation for each data set (Fig. 3). The data in Fig. 3 was obtained by rounding the recorded MDP data values to the nearest integer. If the data is presented in this fashion, it becomes possible to include all of the data that is recorded over an area for a given lift and pass, as the data is not analyzed in a spatially sensitive fashion; e.g., the data shown in Fig. 3 corresponds to the values recorded from three side-by-side roller transects for Pass 3 on Lift 5.

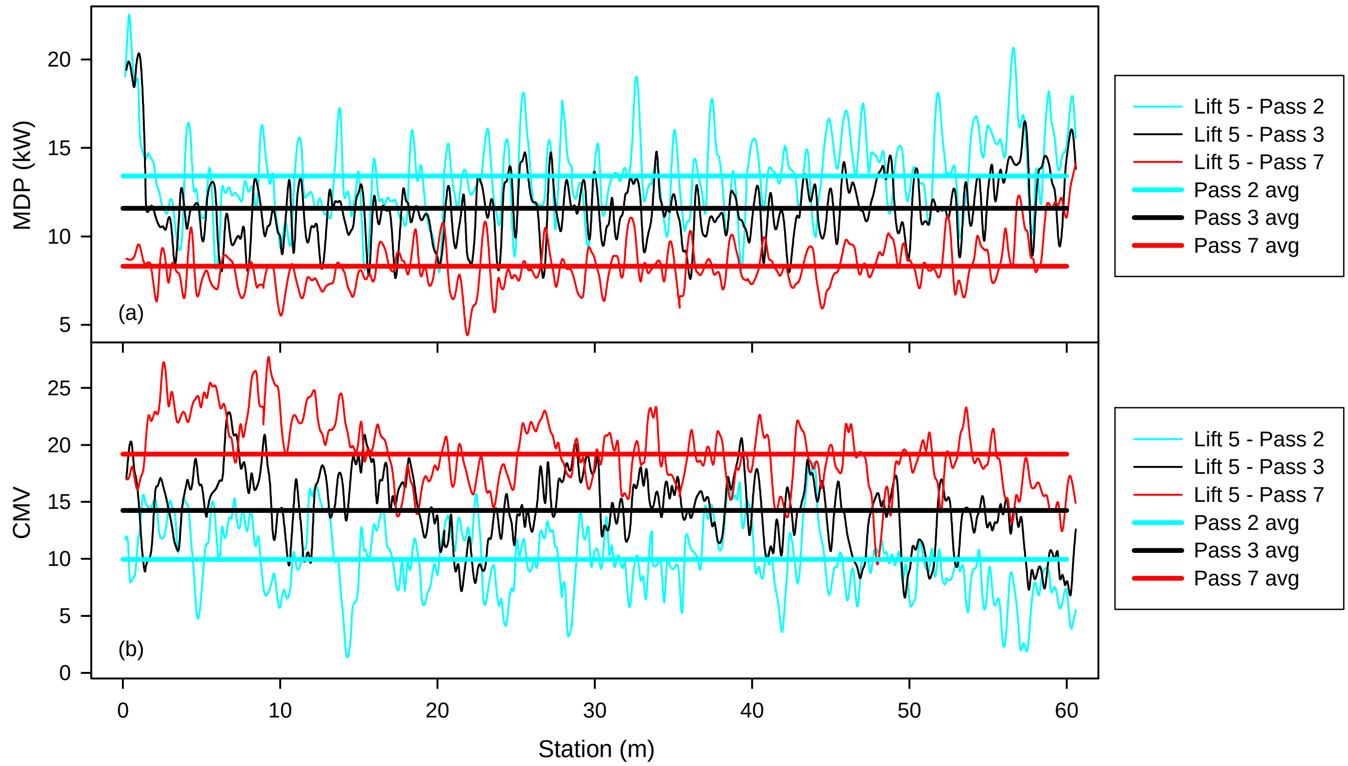

Fig. 2: Variation of MDP and CMV values along the middle transect of Lift 5.

In order to compare the respective shape of the histograms from each lift/pass, the data points corresponding to the midpoint of each histogram bar in a given histogram can be connected to create an approximated histogram "trace" (Fig. 3).

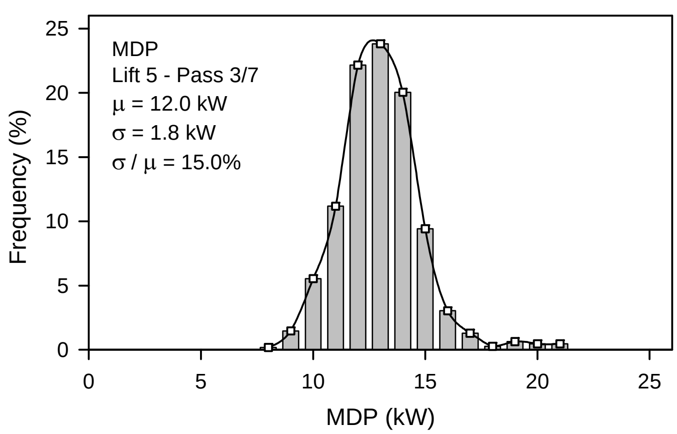

Fig. 3: Histogram of recorded MDP values for Lift 5, Pass 3.

During this study, CCC data was recorded for the final pass of compaction for the base material underlying the test pad and for the final passes of compaction for each lift. (Note: The final pass data for Lift 1 was lost due to a malfunction with the data card reader.) In addition, for the 5th lift, CCC data was recorded and is presented for compaction of the 1st, 2nd, 3rd, 4th, 5th, and 7th passes (out of seven passes total for this lift). Figure 4 and Fig. 5 show a comparison of the resulting histogram traces for the final compactive passes on each lift and the successive passes on Lift 5 for the recorded MDP and CMV data sets, respectively. An alternative approach that can be used to compare the data from different lifts and passes on the same plot would be to present the data in the form of cumulative frequency distributions.

By examining Figs. 4 and 5, it can be observed that the recorded MDP values resulted in relatively "well-shaped" histograms, as compared with the recorded CMV values. This is not surprising, as the recorded CMV values are affected by the characteristics of underlying soil layers, which potentially makes them more variable and which can cause the histogram data sets to have secondary peaks around the mean (Peterson et al. 2006).

As shown in Figs. 4 and 5, analysis of sequential passes on a given lift is quite instructive about the general behavior of the roller-measured values with increasing compactive effort. As shown in Fig. 4, the relative location of the MDP histograms shifts to the left and the distribution become narrower and taller as the number of passes increases. Conversely, CMV values tend to increase with increasing compactive effort (Fig. 5), with a change in variance that is not nearly as clear as what was observed for the MDP values. These observed histogram shifts from pass-to-pass are consistent with the expected MDP and CMV behavior, and are essential for proper field application of these technologies to control the construction process.

Unfortunately, as noted above, the general shape of the CMV histograms is not as clear as what was observed for

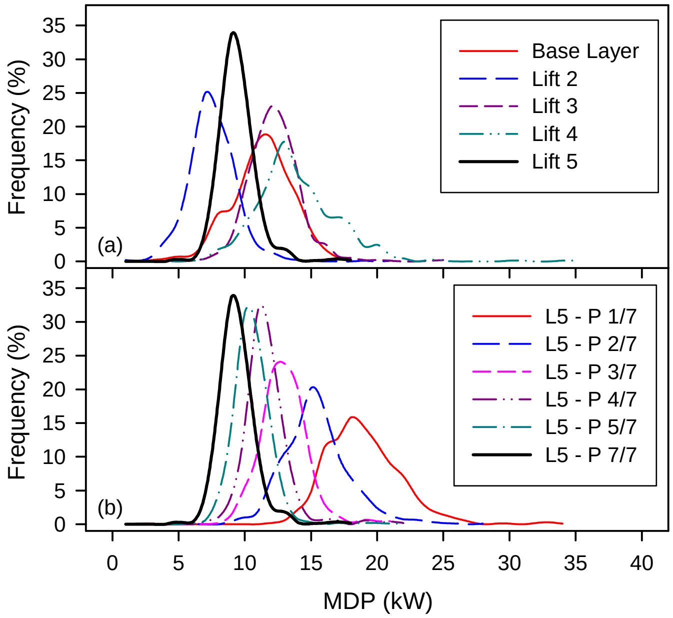

Fig. 4: Histogram traces of MDP values: (a) Final passes; (b) successive passes for Lift 5.

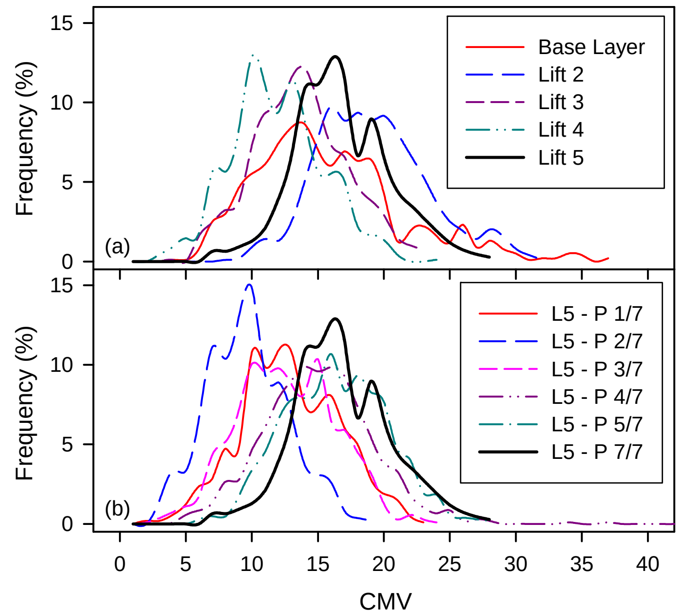

Fig. 5: Histogram traces of CMV values: (a) Final passes; (b) successive passes for Lift 5.

the MDP values, which is likely caused by the influence of underlying layers on the recorded data. Consequently, interpretation of MDP values for a given lift and pass may be more direct and straightforward than interpretation of CMV values, as the results do not appear to be strongly affected by the behavior of underlying layers.

Given the respective histogram shapes from pass-to-pass, interpretation of CMV data may be somewhat more difficult than interpretation of MDP data. This has the potential to make CMV-based construction specifications more difficult to apply uniformly to all projects, where the nature of underlying layers may have variable effects on the measured data for a newly constructed lift. This is of particular concern for field cases where underlying layers may not have been placed by the Contractor (e.g., proof-rolled base layers), and which therefore were out of his or her control. Conversely, the deeper penetrating nature of CMV values tends to capture the behavior of sub-base layers more effectively, and consequently may more accurately reflect the long-term behavior of overlying soil or pavement lifts.

Figure 6 presents the variation of the mean values of MDP and CMV for the final passes on each lift (Fig. 6(a)) and the successive passes on Lift 5 (Fig. 6(b)). As shown, the average values of CMV tend to vary inversely when compared with the corresponding average values of MDP. By examining the sequential passes for Lift 5 (Fig. 6(b)), it is clear that the values of MDP decrease as additional compactive effort is applied to the soil. This is expected, as the gross machine power consumed by the compactor should become less as the soil becomes more compact (White et al. 2005). Average CMV values were observed to increase with increasing compactive effort (Fig. 6(b)), provided that the average data from Pass 1 is disregarded. The reason for the inconsistency in CMV data between Pass 1 and the other passes for Lift 5 arises from the difference in applied vibratory compaction amplitude for these passes. As indicated previously, the first pass of each lift was compacted using high-amplitude vibration (1.87 mm) and the other passes were compacted using low-amplitude vibration (0.85 mm). As noted in Eq 1, the amplitude of the first harmonic of the acceleration response signal ($\hat{a}(2w_0)$) is used to determine the CMV values. This value does not scale linearly with the amplitude of the input vibration ($\hat{a}(w_0)$), which means that the measured CMV values shown in Fig. 6(b) should only be compared for those passes that were compacted using the same amplitude of input vibration (those that were compacted using consistent input vibration energy). This observed effect of compaction amplitude on recorded CMV values is consistent with what has been observed by other researchers (e.g., Mooney and Adam 2007). Consequently, the data from the first pass of Lift 5 is excluded from any of the regression analyses that are described in the remainder of this paper.

The coefficient of variation is a useful normalized, dimensionless statistical value that can be used to compare the variability of data sets of differing units. Figure 7 shows the coefficient of variation values for each of the MDP and CMV data sets, for the final passes of each lift and for successive passes on Lift 5. As shown, relatively significant lift-by-lift variability was observed in the coefficient of variation values, without a clear trend in behavior. However, for a given lift, the pass-by-pass behavior was much more consistent: MDP coefficients of variation were relatively constant, which means that the standard deviation of the data set changed in proportion to its mean, and the CMV coefficients of variation decreased with increasing compactive effort (CMV data for Lift 5, Pass 1 is presented here for the readers' interest, but should not be considered when looking at overall trends in behavior, for reasons noted in the preceding paragraph). In gen-

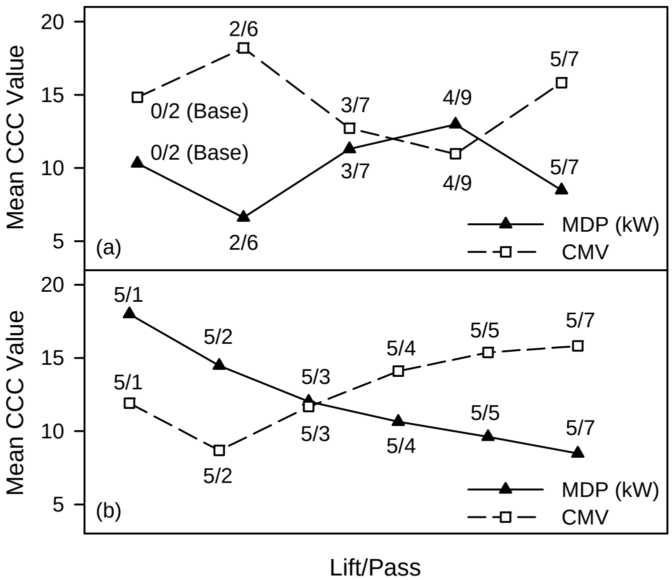

Fig. 6: Mean value of the roller measurements: (a) Final passes; (b) successive passes for Lift 5.

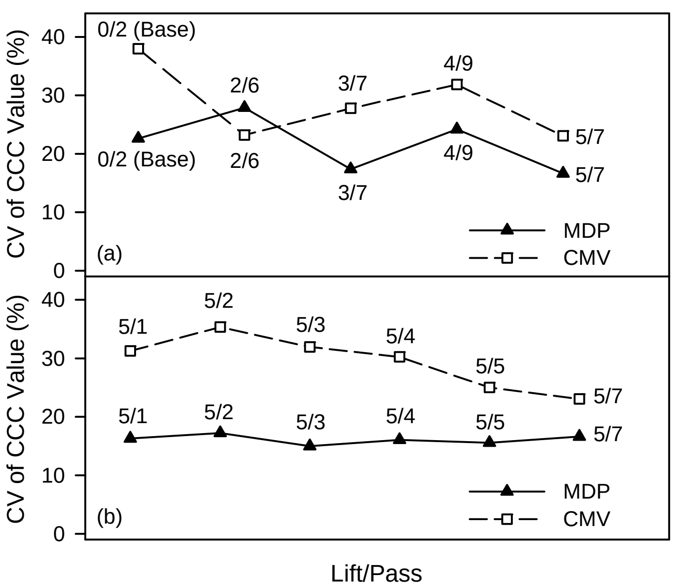

Fig. 7: Coefficient of variation of the roller measurements: (a) Final passes; (b) successive passes for Lift 5.

eral, the recorded CMV values had a significantly larger coefficient of variation than did the corresponding MDP values. This is not surprising, as CMV values are significantly affected by the stiffness of underlying layers, and consequently more sophisticated analyses are warranted to develop a more complete understanding of their behavior.

5 Statistical Nature of Recorded CCC Data / Distribution Fitting

In order to develop a more robust understanding of the statistical nature of the CCC data that was recorded, it was useful and informative to employ statistical techniques to compare a variety of theoretical distributions to the measured data; this process is commonly referred to as distribution fitting. Figures 8 and 9 show typical quantile-quantile (Q-Q) probability plots (e.g., Baecher and Christian 2003; Tukey 1977; Hoaglin et al. 2000) that compare the measured sample quantiles for Lift 5, Pass 7 (the measured MDP and CMV values, respectively) with theoretical quantiles that correspond to a variety of commonly used statistical distributions. In each figure, Q-Q plots are presented for the normal (Gaussian), lognormal, exponential, Weibull, gamma, and logistic probability distributions. These theoretical distributions were selected because they are all commonly used mathematical distribution functions, they correspond to continuously varying data (as opposed to discrete data), and they all have a range that is either semi-infinite or unbounded. In these figures, a total of 1,095 data points are compared versus each of the theoretical distributions ($N = 1{,}095$ for Lift 5, Pass 7). The straight line shown on each plot is drawn by connecting the first and third quartiles of the data set. This technique can be used to visually asses the linearity of the data on each Q-Q plot; deviations from this represent deviations between the measured sample behavior and the theoretical distribution.

As shown in Figs. 8 and 9, the lognormal and exponential probability distributions are clearly not a good fit for the recorded MDP and CMV values. The logistic distribution fits relatively well for both data sets over the middle of the data range, but has a little trouble at both the upper and lower ends; in general, the logistic model fits better for the CMV data than for the MDP data (though this trend was not observed for all of the other data sets that were examined). The recorded MDP and CMV data appears to have approximately the same quality of fit to the theoretical normal, Weibull, and gamma distributions, with model fit results that are better than the logistic distribution. For the MDP values, the measured data deviates rather significantly from the theoretical normal, Weibull, and gamma distributions at the upper end of the data range, with a good quality of fit at all but a few points over the middle and the lower end of the data range. The recorded CMV values tend to fit the normal, Weibull, and gamma distributions more closely over the entire range of recorded data, with the normal distribution tending to show the highest quality of fit.

Although the shape of the Q-Q plots are somewhat different for the remaining lifts and passes for which data was recorded, the authors are comfortable applying the same general observations and conclusions that were made in the previous paragraph for Lift 5, Pass 7 to the Q-Q plots for the remaining lifts/passes. As a result of this data analysis, it appears as if the normal distribution is as good as, or better than, any of the other commonly used statistical distributions that were examined for theoretical representation of the MDP and CMV data recorded during this study.

To explore this hypothesis further, and to assess whether or not the recorded data can be assumed to have been sampled from a normally distributed data set, a number of commonly used "normality tests" were ap-

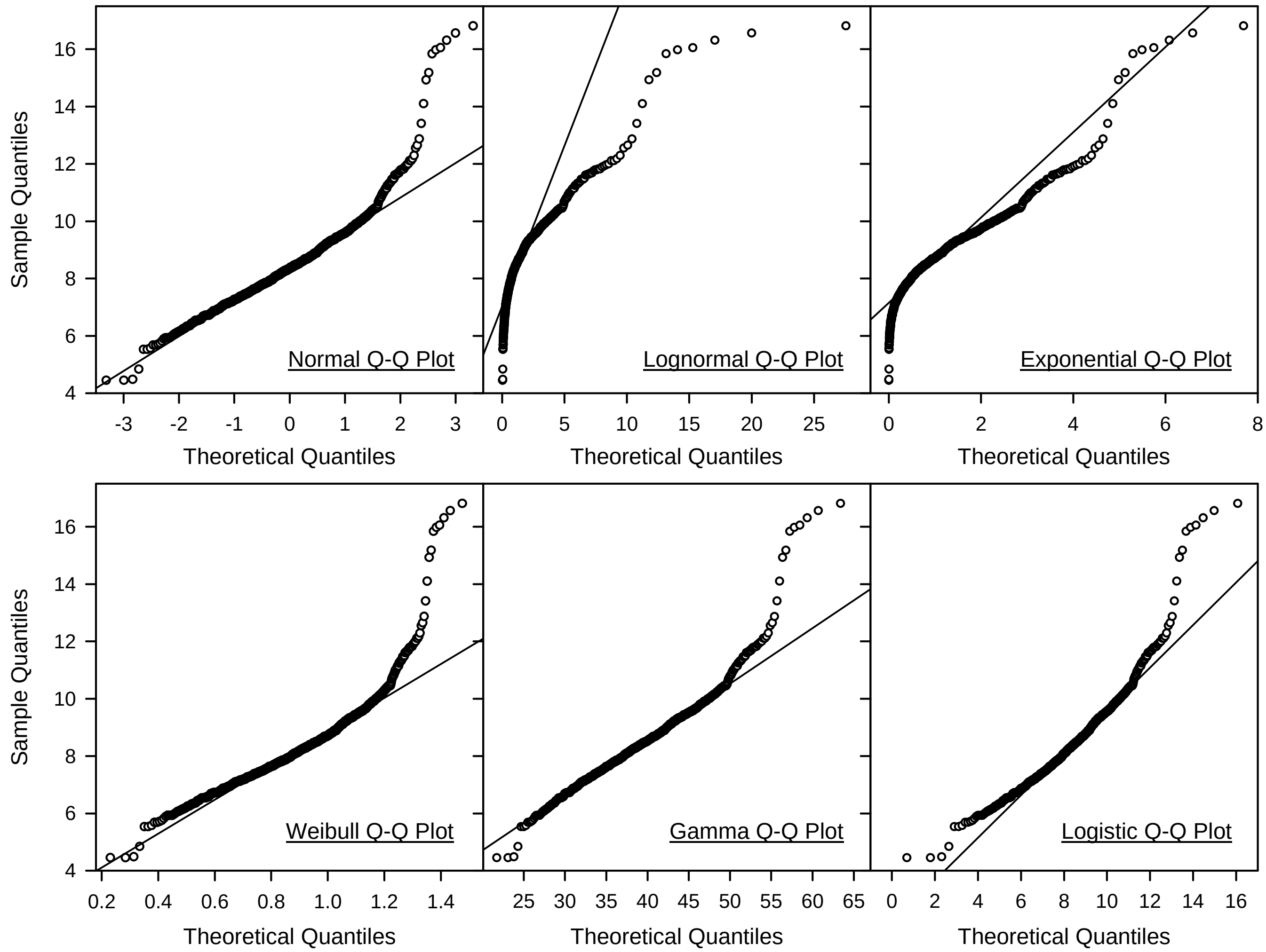

Fig. 8: Typical Q-Q probability plots: Sample MDP quantiles for Lift 5, Pass 7 versus idealized distribution quantiles.

plied to the recorded MDP and CMV data sets. The tests that were used include the Shapiro-Wilk test (Shapiro and Wilk 1965), the Shapiro-Francia test (Shapiro and Francia 1972), the Anderson-Darling test (Anderson and Darling 1952), and the Lilliefors test (Lilliefors 1967). Results from these tests indicated that the hypothesis of normality for the MDP and CMV data sets can be rejected.

Based on the four statistical tests that were conducted, each of the MDP and CMV data sets failed to meet the required level of significance to state that this data was sampled from a normally distributed population. However, the Q-Q plots do seem to suggest, albeit qualitatively, that, of the six distributions that were tested, the normal distribution appears to give the best description of the MDP and CMV data. Examination of the normal Q-Q plots in Figs. 8 and 9 also provides the following useful information.

First, that a large majority of the recorded MDP and CMV data corresponds quite closely to values that might have been recorded from a normally distributed data set. Thus, although the MDP and CMV lift/pass data sets fail to satisfy the criterion of "statistical significance" that is commonly used for hypothesis-based normality testing in many other disciplines, the approximation that the data was sampled from a normally distributed data set may be reasonable enough for certain geotechnical engineering applications, such as writing QA/QC compaction specifications.

Second, that more data points diverge from normality for the CMV data than for the MDP data, but by a much smaller relative amount. Another way of saying this is that fewer MDP values diverge from normality than what was observed in the CMV data set; however, those values that diverge do so by a significant amount. Interestingly, the divergence from normality that was observed tended to be for values on the high-end of the recorded data spectrum for both types of recorded data (e.g., MDP values > 10.5 or so, and CMV values > 20 or so).

Third, that when recorded data values for both the MDP and CMV data sets diverged from the normal distribution, the recorded values tended to be larger than the corresponding normal distribution values.

In general, the aforementioned observations which were made for the Lift 5, Pass 7 data set were applicable to the other recorded MDP and CMV data sets as well. It

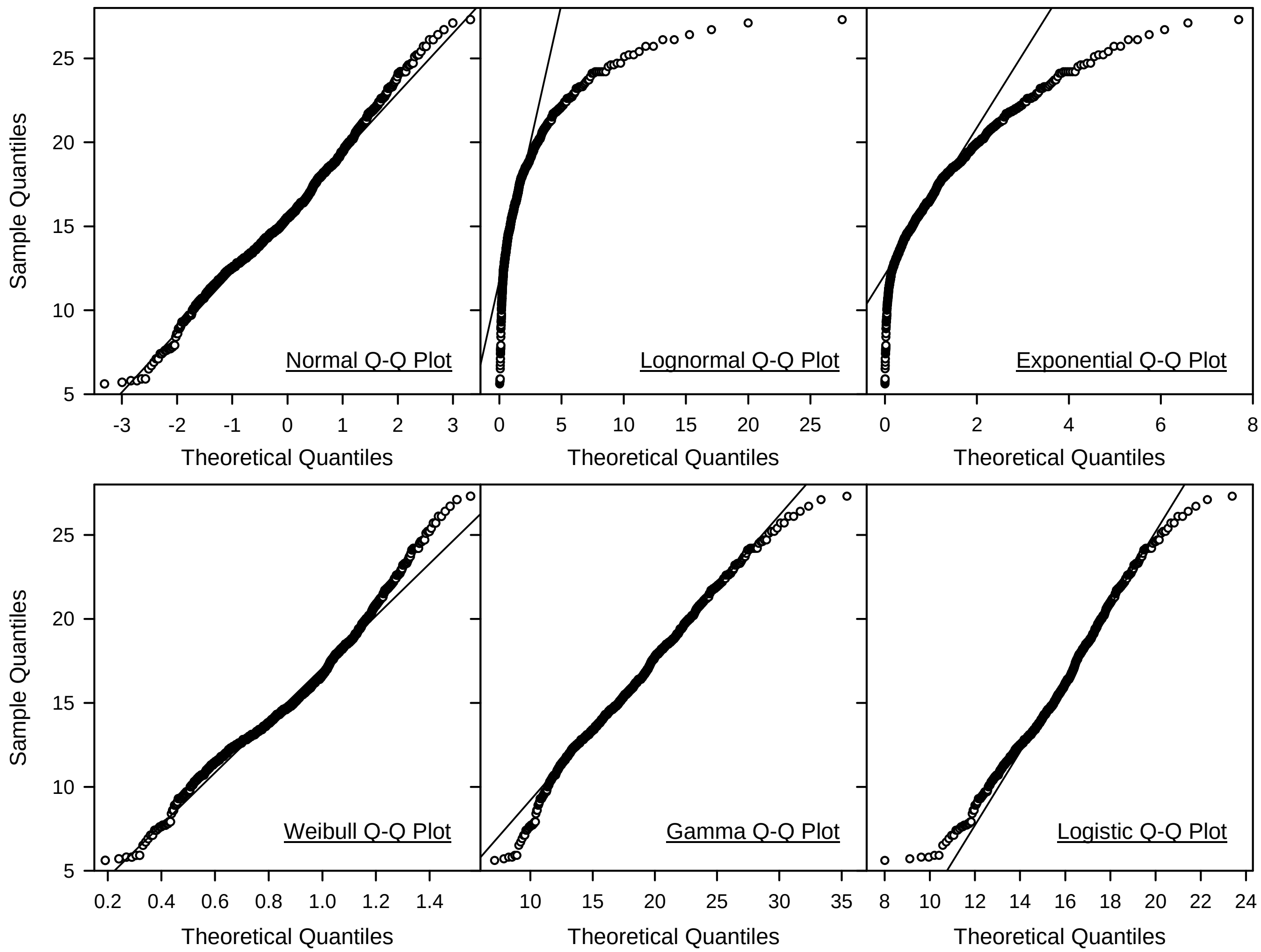

Fig. 9: Typical Q-Q probability plots: Sample CMV quantiles for Lift 5, Pass 7 versus idealized distribution quantiles.

is important to understand and interpret these deviations from normality in a practical context. When imposing compaction control criteria, it is going to be the "failing" points at the tail end of each distribution that are going to be of the most concern. For example, CMV values that tend to be larger than the normal values at the high-end of the recorded data spectrum are of little concern, as these points correspond to the highest amount of energy return from the underlying soil, which is likely to be your "best-quality" or at least your "better-than-average" quality compacted soil (depending upon the nature of the underlying layers, and how they influence your recorded CMV values). In contrast, MDP values that are larger than the normal values at the high-end of the recorded data spectrum are of great concern, as high MDP values are indicative of a greater resistance to compactor rolling, and consequently correspond to your most poorly compacted soil.

The practical implications of these deviations from normality need to be understood when imposing percentage-based passing criteria when writing CCC or IC specifications that are to be used to control the construction process (e.g., a desirable specification approach might be to say that 80 % of the recorded data points must be smaller than (MDP) or larger than (CMV) a pre-specified target value from test pad construction). These data indicate that it may not be reasonable to use the same percentage passing criteria for different types of CCC indicator values (e.g., MDP, CMV, etc.), as these data are sampled from distributions that are different from normal, and more importantly, different from each other.

6 Relationships Between Recorded MDP and CMV Data

An alternative approach for comparing the recorded MDP and CMV data sets is much more direct than using the distribution assessment techniques described in the previous section. As each of the MDP and CMV data points were simultaneously recorded, it is possible to directly plot the recorded data against each other, as shown in Fig. 10. As can be observed, there is large scatter when these data sets are directly compared; the same behavior was observed for each of the data sets that were recorded for each lift and pass. The lack of correlation between these values was initially somewhat surprising, as the general trends in the average MDP and CMV values shown in Fig. 6(a) and 6(b) appear to mirror each other almost exactly. This observation prompted the authors to perform a regression analysis on the average MDP and CMV values for each lift and pass (Fig. 11).

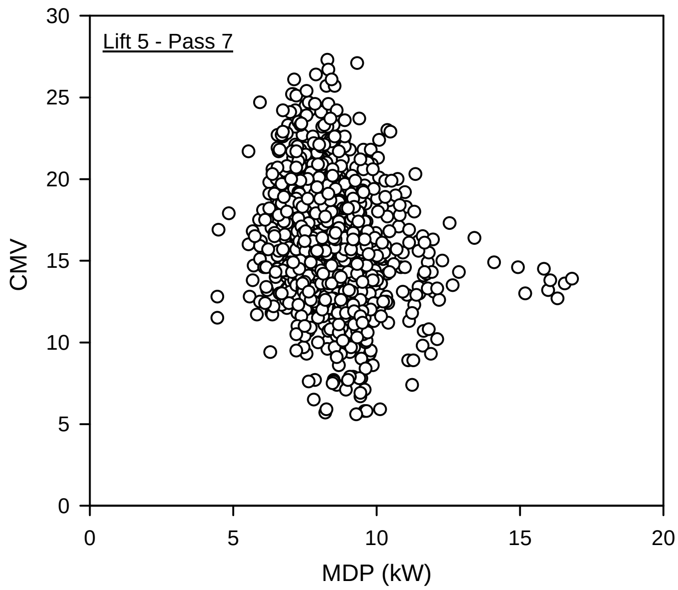

Fig. 10: A comparison of CMV and MDP values for Lift 5, Pass 7.

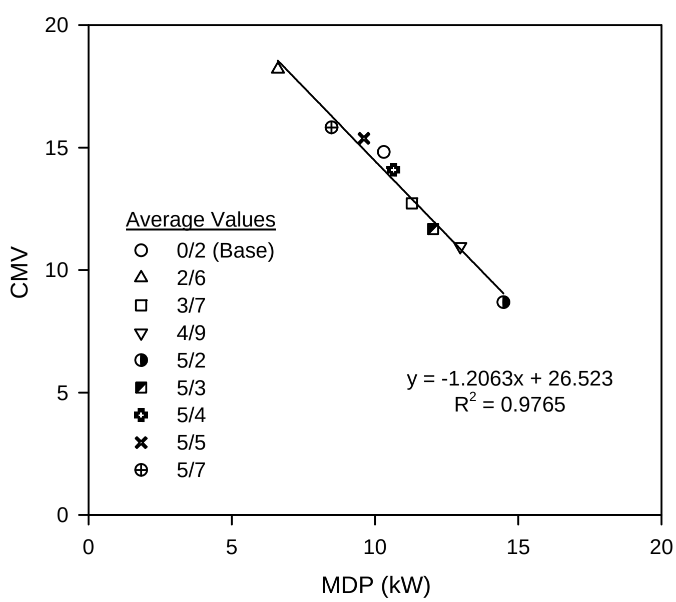

Fig. 11: Linear regression analysis of average CMV and MDP values for each lift/pass.

As shown in Fig. 11, there is a strong inverse linear relationship between the average MDP and CMV values for each lift and pass. This relationship exists despite extremely poor point-to-point correlation between the individual MDP and CMV values that were recorded. These findings are generally consistent with those reported by White and Thompson (2008), who used the same general approach for data analysis, and who recommended a logarithmic functional form for the average CMV/MDP relationship. The tremendous amount of point-to-point scatter that was observed in the individual MDP and CMV value comparisons is attributed to: the effect of underlying soil layers on recorded CMV values, natural variability in the grain size and mineralogy of the material that is being compacted, variations in the compaction water content, and natural errors that occur in the data acquisition process (e.g., electronic signal noise). The relationship shown in Fig. 11 is unique for a given soil, compactor type, and set of site conditions (e.g., underlying layer characteristics); consequently, relationships of this form will need to be developed for each new site that is analyzed.

It should be noted here that many commonly used statistical analysis methods (e.g., t test, ANOVA, least-squares regression, etc.) depend on the assumption that the underlying data were sampled from a normal (Gaussian) distribution. As the Q-Q plots and normality tests that were described in the previous sections have indicated that each of the MDP and CMV data sets were likely not sampled from normally distributed populations, any results from least-squares regression analyses should be interpreted with caution. Other practitioners and researchers working in this area are recommended to use the techniques described herein to test the normality of their data, and should keep their results in mind when interpreting the findings from any associated regression analyses that they might perform. In some cases, more sophisticated regression analysis techniques may be warranted, or it may be necessary to "clean" the data as part of the analysis process.

7 Summary and Conclusions

An experimental research study was conducted to evaluate the performance of compaction equipment that utilizes both machine power-based and vibratory-based measurements for quality control of the compaction process. During this study, a road sub-base test pad was constructed and compacted by a smooth drum roller in a series of lifts, while simultaneously recording machine drive power (MDP) and compactometer (CMV) indicator values. The soils utilized for construction were granular in nature, and classify as either poorly-graded sand with silt (SP-SM) or silty sand (SM). This paper presents the measured MDP and CMV results from the field study that was performed. The following conclusions were drawn from the data that is presented and analyzed:

1. There is significant spatial variability in recorded MDP and CMV values, which makes point-specific (location-specific) comparisons from pass-to-pass quite difficult. This behavior will also likely make it rather difficult to compare CCC roller measurements directly with more traditional in situ test results such as nuclear density gauge measurements of soil density. Relatively sophisticated spatially oriented data analy-

sis tools such as kriging will consequently be necessary for these sorts of analyses.

2. Recorded MDP values for a given lift and pass tend to yield relatively "well-shaped" histograms, when compared to recorded CMV values. This behavior is attributed to the fact that CMV values are affected by the characteristics of underlying soil layers, which makes them more variable and which causes the histogram data sets to have secondary peaks around the mean. Given the respective histogram shapes from pass-to-pass, interpretation of CMV data may be somewhat more difficult than interpretation of MDP data. This has the potential to make CMV-based construction specifications more difficult to apply uniformly to all projects, where the nature of underlying layers may have variable effects on the measured data for a newly constructed lift.
3. For a given compaction lift, with increasing compactive effort, average MDP values consistently decrease and CMV values consistently increase following predictable trends. Measured CMV values should only be compared for those passes that were compacted using the same amplitude of input vibration energy. For a given lift, the coefficient of variation of the recorded MDP values remained relatively consistent from pass-to-pass, while the coefficient of variation of the recorded CMV values decreased.
4. Of the six statistical distribution types that were examined using Q-Q plots (normal, lognormal, exponential, Weibull, gamma, and logistic), the normal distribution appears to provide the best theoretical representation of the MDP and CMV data recorded during this study. Where the recorded data values for the MDP and CMV data sets diverged from the normal distribution, both types of recorded values tended to be larger than the corresponding normal distribution values. Other observations that were made from the Q-Q plots have practical implications when imposing percentage-based passing criteria in CCC or IC specifications, as they indicate that it may not be reasonable to use the same percentage passing criteria for different types of CCC indicator values (e.g., MDP, CMV, etc.).
5. Direct comparisons of the simultaneously recorded MDP and CMV values show that there is essentially no relationship between the values on a point-by-point basis. Interestingly, however, comparisons between the averages of the recorded values for each lift and pass yielded a strongly linear relationship. These results are consistent with those that have been reported by others for this type of CCC data.

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Nomenclature

The following symbols are used in this paper:

a = acceleration of the compactor;
$\hat{a}(w_0)$ = amplitude of the exciting frequency of vibration during vibratory compaction;
$\hat{a}(2w_0)$ = amplitude of the first harmonic of the acceleration response signal during vibratory compaction;
α = slope angle;
b = machine internal loss coefficient specific to a particular compactor;
C = constant value chosen to empirically scale the output CMV values to an easier-to-interpret range;
g = acceleration of gravity;
m = machine internal loss coefficient specific to a particular compactor;
P_g = gross power needed to move the compactor through an uncompacted layer of fill;
P_n = net power required to propel the compactor through an uncompacted layer of fill;
V = compactor velocity;
W = compactor weight.

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