PROXIMAL SENSING OF DENSITY DURING SOIL COMPACTION BY INSTRUMENTED ROLLER

Amir Tophel, Jeffrey P Walker, Ye Lu and Jayantha Kodikara
Monash University, Clayton

https://doi.org/10.56295/AGJ5739

ABSTRACT

The measurement of density or void ratio during the compaction of geomaterials (soils and unbound granular materials) in the field during road construction is essential for superior performance. The specifications adopted by the road authorities worldwide are exclusively based on density. However, estimating density evolution proximally or non-destructively is challenging. Conventional field-based density measurement techniques are hazardous, slow to use and are point-based measurements.

This study developed a novel methodology to estimate the density of geomaterials non-destructively in real-time during the compaction process. The methodology included measuring the surface deformation using Light Detection and Ranging (LiDAR) systems attached to rollers and developing physics-based 1-Dimensional and machine learning (ML) based constitutive models to relate the measured parameters to the density. The developed methodology was validated in an indoor environment where a large soil box (dimensions: 7.5 m×4 m×0.8 m) was fabricated and a well-graded sand in 5 layers of 100 mm was compacted using a 1.5-tonne instrumented roller. The measurement of deformation provided an opportunity to estimate the density in real-time. The estimated density using 1-D model and a ML based classification model had an error of 20% and 16% respectively when compared to density measured from Nuclear Density Gauge (NDG).

This novel instrumentation allowed the density to be measured during compaction with high accuracy, which presents an unprecedented advantage over other conventional approaches, which are intrusive and pointwise, thereby ensuring that the road will be constructed expediently and will function satisfactorily, minimising the occurrence of premature failures. The continual measurement of density during compaction will also facilitate maintaining uniformity of the density, thereby reducing the potential for excessive differential deformations.

1 INTRODUCTION

The structural capacity of a flexible pavement depends on the mechanical properties of the constituting layers. The flexible pavement has multiple layers, and the materials of each layer are compacted to ensure that they attain sufficient strength for sustaining the traffic load during its service life (Kodikara, Islam and Southararajah, 2018). The materials are compacted using different rollers depending on the material being used. The compaction process involves mixing the material with the required amount of moisture near their Optimum Moisture Content (OMC) and then compacting using the rollers. The compaction of loose material involves reducing air content from the material matrix and densifying it. The degree of compaction is evaluated by measuring density. Measurement of soil density and moisture content is essential for Quality Assurance (QA) and Quality Control (QC) of the earthwork. It has also been recommended by most road authorities in Australia and government Department of Transportation organisations worldwide. The QA/QC for Australia is shown in Table 1.

The methods to assess the QA/QC of pavements can be divided into three main types

a. Intrusive or destructive: Nuclear Density Gauge (NDG), Sand replacement test, Rubber balloon density test, Borehole shear tester, Dynamic cone penetrometer, Panda probe, Static plate load test, Electrical resistivity test, GeoGauge and Clegg hammer
b. Non-intrusive surface-based measurement: Falling weight deflectometer, Moisture and density indicator, Electrical density gauge, and Portable seismic Pavement analyser (Nazzal, 2014)
c. Proximal estimation: (Ground penetrating radar and Intelligent Compaction (IC))

1.1 ISSUES WITH THE CURRENT QA/QC MEASUREMENTS

Intrusive are the types of methods that require sampling or disturbing the area by hammering or inserting the measurement system. The sampling area is then filled with soil, and the region is recompacted manually. Intrusive methods such as sand replacement, rubber balloon density, and borehole shear tester are lag indicators of the density. It can take around 2-7 days for the result to be available, and the depth of excavation is limited to about 300 mm (Lee, Lacey and Look, 2017). Dynamic cone penetrometer, Panda probe, Static plate load test, GeoGauge, and Clegg hammer are the indirect measure of the density. Measurements such as blows per minute for Dynamic cone penetrometer, stress-strain relationship in GeoGuage, and static plate load test are indirectly correlated to density (Caicedo, 2019). Electrical resistivity test measures the electrical resistivity and then relates it to density and moisture content (Neyamadpour, 2019; Swileam *et al.*, 2019; Yuan, Che and Feng, 2020). Pandey et al. 2015 showed that the electrical resistivity of soil is a function of both density and moisture content.

Table 1: QA/QC recommendation by road authorities in Australia (Latter, Rice and Andrews, 2019)

Road Authority	Test	Standard
VicRoads, VIC	Nuclear Gauge	AS1289.5.8.1
Department of Planning, Transport and Infrastructure, SA	Nuclear Gauge	AS1289.5.8.1
Main Roads Western Australia, WA	Nuclear Gauge and Sand replacement	WA 324.1, WA 324.2
Roads and Marine Services, NSW/ACT	Sand replacement and Fixed volume extractive method	T119, T165
Queensland Department of Transport and Main Roads	Relative compaction, Density index	Q140A, AS1289.5.5.1, AS1289.5.6.1
Department of State Growth, TAS	Nuclear Gauge and Sand replacement	AS1289.5.8.1, AS 1289.5.3.1, AS 1289.5.3.2
Department of Infrastructure, Planning, and Logistics, NT	Nuclear Gauge	NTP 102.1

The main drawback of using NDG is that it emits harmful radiation, and prolonged exposure is detrimental to human health. This has limited use and requires an additional licence to purchase (Latter, Rice and Andrews, 2019). Moisture and density indicator, Electrical density gauge, and Portable seismic Pavement analyser can measure both density and moisture content. However, they are very complex to operate and require extensive operator training (Weber, 2018).

GPR response of soil, similar to electrical resistivity test is used to estimate density, however they are found to have a relationship with both water content and density and resolving the effects of the two has been difficult (Plati and Loizos, 2013). In Intelligent Compaction (IC) the roller is integrated with temperature sensors, an accelerometer, Global Positioning System (GPS), and a display monitor. The continuous GPS and accelerometer data recording provide a user with real-time information about the compaction degree.

The recorded drum response is used to calculate different Intelligent Compaction Measurement Values (ICMVs) that are correlated with density. The correlation between ICMVs and density is poor; however, the correlation between ICMVs and modulus is better for some range of material moisture content (Zargar and Lee, 2019; Hu *et al.*, 2020). The other constraints with using the IC technique are that:

a) ICMVs are directionally dependent, and the values differ significantly if the direction of travel of the roller is reversed (Facas, Rinehart and Mooney, 2011)

b) ICMVs are dependent on the machine operating parameters (vibration amplitude (A), excitation frequency (f), and roller speed) and require them to remain constant during measurement passes (Adam and Kopf, 2004; Mooney and Rinehart, 2009).

Therefore, a need for a methodology for the proximal estimation of density in the field arises. The method would allow the contractor or the field practitioner to check compaction quality in real time.

The primary purpose of this research is to explore and provide a novel proximal density measurement technique that can be used in real-time. The proposed methodology for estimating the density assumes the reduction of the layer's thickness (surface deformation) during compaction as the vital indicator of the level of compaction achieved (Wersäll and Larsson, 2013; Wersäll *et al.*, 2015). The framework has been developed based on observation of the material being compacted. When a material is compacted, the thickness of the material reduces and the density increases. Sufficient density has been achieved when material deformation falls below a prescribed limit. The methodology is framed with this observation and the possibility of measuring the deformation and then relating it to the density (Tophel, Kodikara and Walker, 2021). Figure 1 illustrates the state of the material before and after a pass by a roller.

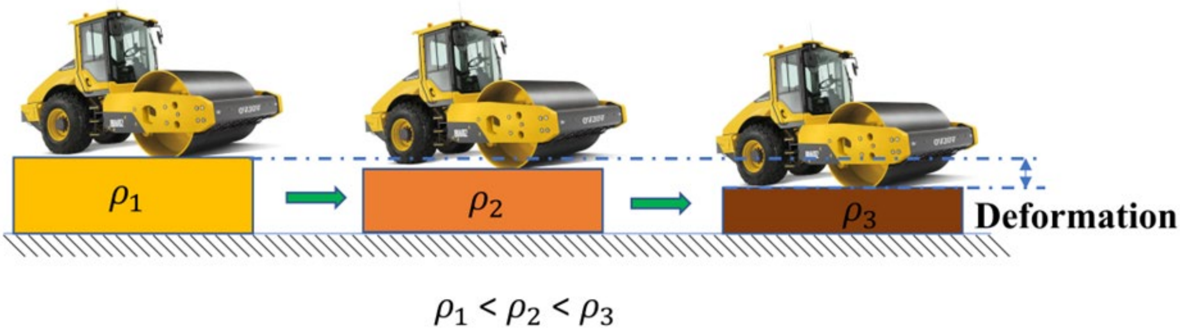

Figure 1: Illustration of material deformation during compaction and increase in density (ρ)

2 METHODOLOGY

The proposed methodology involves measuring the deformation during the compaction using multiple Light Detection and Ranging (LiDAR) systems attached to the roller. The deformation measurement estimates the density in real-time using a simple 1-Dimensional model and a machine learning (ML) based classification model.

2.1 INSTRUMENTATION TO MEASURE THE SURFACE DEFORMATION

Sensors include two LiDAR systems and a positioning system used to measure the deformation during compaction. The concept is presented in an idealised form in Figure 2, illustrating that using two LiDAR, one at the front of the drum and the other at the rear of the drum, the deformation during the compaction can be measured, being $D_b - D_a$. An overview of the instrumentation on the roller is illustrated in Figure 3.

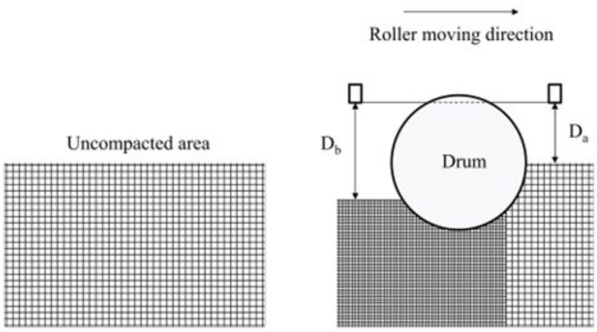

Figure 2: Material compaction using roller and deformation measurement using LiDAR systems during compaction

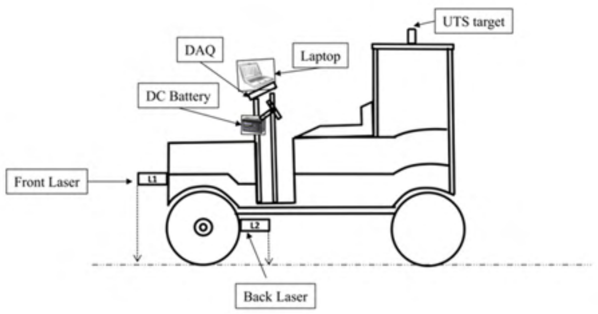

Figure 3: Schematic of the instrumented roller used for this study

The roller was instrumented with two triangulation LiDAR sensors, one attached to the front of the front drum and the other attached to the rear of the front drum. The roller was also equipped with Universal Total Station (UTS) target to record the position of the roller instead of GPS as this was an indoor setting. The sensors acquired all data via a 16-bit, 250-kHz data acquisition (DAQ) system manufactured by National Instruments connected to a windows-based Dell Precision 5530 laptop PC. The PC was equipped with National Instruments' Laboratory Virtual Instrument Engineering Workbench (LabVIEW), a visual programming language environment. LabVIEW was used to acquire all the signals and analyse real-time signals. The details of LiDAR sensors used are summarised in Table 2.

Table 2: Electrical details of the LiDAR/laser sensor used for this study

Instrument	LiDAR
Manufacturer	OMRON Corporation
Model	OM70-L1000.HV0700.VI
Sampling Frequency (Maximum)	2.5 kHz
Rated capacity/ Measuring range	100-1000 mm
Sensitivity/Resolution	3-63 µm
Output circuit	Analog and RS 485
Voltage supply range (VDC)	+15 to +28
Output signal (VDC)	+4 to +20 mA / 0 to +10
Temperature Error	0.065 % So/K (-10 to 50 °C)
Dimensions, mm	26×55×74

2.1.1 Laser/LiDAR systems

Triangulation displacement LiDAR line sensor type are used for this study. In the triangulation principle, the sensor transmits a beam of light to the object to be measured, and the reflected light strikes the receiver line in the detector at a unique angle. Depending on the angle of incidence, the distance to the object is calculated. The light source for the laser used was a pulsed red laser diode with a 600 nm wavelength. The laser beam is classified as class 2, which makes it safer to use. The beam characteristic of the laser is shown in Figure 4. As the LiDAR measuring range was 100 mm to 1000 mm, the laser beam characteristics study was important to achieve the highest accuracy from the sensors.

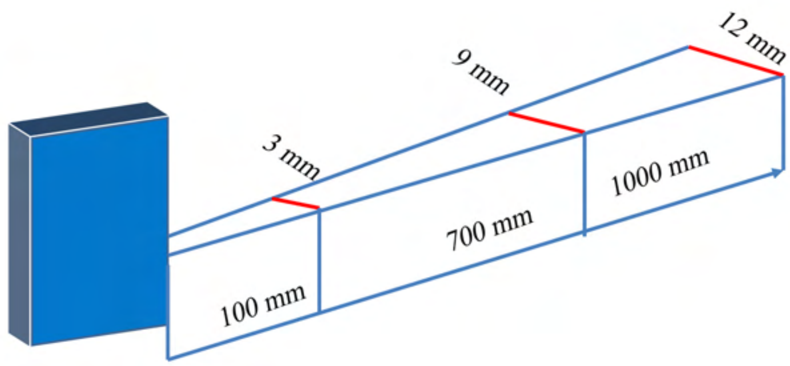

Figure 4: Typical beam characteristics of the LiDAR used (not drawn to scale)

2.2 DENSITY ESTIMATION

2.2.1 Density estimation using 1-D relationship

Using the linear relationship between height change and density change

The dry density (ρ_f) using the deformation measured is calculated using a simplified 1D equation shown below:

$$\frac{\Delta H}{H_0} = \frac{\rho_f - \rho_0}{\rho_f}, \quad (1)$$

where ΔH is the deformation measured using LiDAR, H_0 is the initial layer thickness measured using optical level and staff, ρ_0 is the initial layer density measured using NDG, ρ_f is the final density.

2.2.2 Density estimation using ML Model

To consider the nonlinear relationship between the height change and the density change, a data-driven machine learning (ML) approach is considered for this study. The algorithm used for this analysis is Scikit-learn's Stochastic Gradient Descent (SGD) Classifiers; this was implemented in Python along with other modules required, including Pandas, Numpy, and Seaborn, which were used to implement the model (Van Rossum and Drake Jr, 1995; McKinney and others, 2010; Pedregosa *et al.*, 2011; Harris *et al.*, 2020). SGD classifier is one of the supervised ML models used for classification and uses the Stochastic Gradient Descent algorithm to minimise the loss function. The classification differs from regression as it is the task used to predict the discrete class label, whereas regression is used to predict a continuous quantity. For this study, the input parameters were the same as the 1-D model: the initial height, the initial density, and deformation, and the two-classification output class were density more than MDD or density less than MDD. So, based on the input, the SGD classifier tried to predict correctly if the density was more than MDD or less than MDD by changing the model parameters during training.

The entire dataset was divided into 80% training data used for developing the model and 20% test data, used for validating the model. The SGD classifier is not discussed in detail in this paper, and the explanation can be found in any standard textbook; for example, see (Géron, 2017).

2.3 TEST METHOD

The tests involve placement and compaction of soil in layers with compacted thickness of 100 mm. The material compacted throughout this study was characterised as sand with silty fines; the other geotechnical properties are listed in Table 3. The soil for this study was mixed with 8% of moisture content and the material was homogenized using a concrete mixer.

Table 3: Geotechnical properties of the material used

Geotechnical property	Value	Standard
Specific gravity (G_S)	2.70	AS 1289.3.5.2 (Standards Australia, 2002)
Median diameter (D_{50}) mm	0.32	AS 1289.3.6.1 (Standards Australia, 2009)
Fines content (%)	20	AS 1289.3.6.1 (Standards Australia, 2009)
MDD standard proctor (Mg/m^3)	1.96	AS 1289.5.1.1 (Standards Australia, 2017)
OMC standard (%)	9.8	AS 1289.5.1.1 (Standards Australia, 2017)
MDD modified Proctor (Mg/m^3)	2.08	AS 1289 5.2.1 (Standards Australia, 2003)
OMC modified Proctor (%)	8	AS 1289 5.2.1 (Standards Australia, 2003)
Optimum degree of saturation (S_{ropt}) (%)	70	AS 1289.5.1.1 (Standards Australia, 2017)
USCS classification	SM	AS 1289.3.6.1 (Standards Australia, 2009)

The site was an indoor facility at Monash University premises which was used to reduce the error coming from outdoor environment. The site included fabricating a large wooden box with dimensions (7.5 m in length, 4m in width and 0.8 m in height) and an additional open area for the ramp for movement of the roller into the box, as shown in Figure 5.

The sides of the box were adequately braced, as shown in Figure 5(b) and 5(c), with wooden angle brackets at a spacing of 125 mm. This was done to ensure the safety of the box during roller vibration at the time of compaction of the soil layer in the box. The structural capacity of the box was also designed with a factor of safety of more than 5.

(a) Schematic diagram (b) Fabricated Large soil box (c) AutoCAD diagram of the site

Figure 5: Pictures of the test site used for this study

The overall test procedure is summarised in Figure 6. The roller used for this study was a 1.5t roller in weight and the other specification is summarized in Table 4.

Table 4: Roller specifications

Specification	Description
Manufacturer	HAMM
Model	HD 10C VV
Type	Articulated tandem roller with two vibratory drums
Total length (mm)	2260
Width (mm)	1056
Roller drum width (mm)	1000
Drum diameter (mm)	620
Speed range (km/h)	0 to 11
Theoretical gradeability	30 % (vibration ON), 40 % (vibration OFF)
Static Mass (kg)	1670
Static Drum Linear Load, front/rear (kg/cm)	8.1/8.6
Vibration frequency (Hz)	52
Amplitude (mm)	0.45
Centrifugal force (kN)	16

(a) Placing the material using a bobcat

(b) Spreading the material manually using shovels and rakes and levelling using a bubble level

(c) Compacting the material using the instrumented roller

(d) Insitu tests for material density and modulus measurement

Figure 6: Test procedure adopted for this study

3 RESULTS AND DISCUSSION

As stated earlier, five layers were compacted and each layer was divided into three lanes based on the dimension of the roller and each lane was divided into $1m^2$ grid area using five points. To minimise the boundary effect, for the outer lanes, around 500 mm distance was kept from the side of the box. Therefore, total number of datapoints were 75 for the entire test. For each point, NDG was performed to collect density data which was used for validation. The comparison between the measured and predicted for density is shown in Figure 7, which shows that the predicted density produces a Mean Absolute Error (MAE) of only 0.08 Mg/m^3. The wet density obtained from NDG was converted to dry density using the moisture content determined from collected samples.

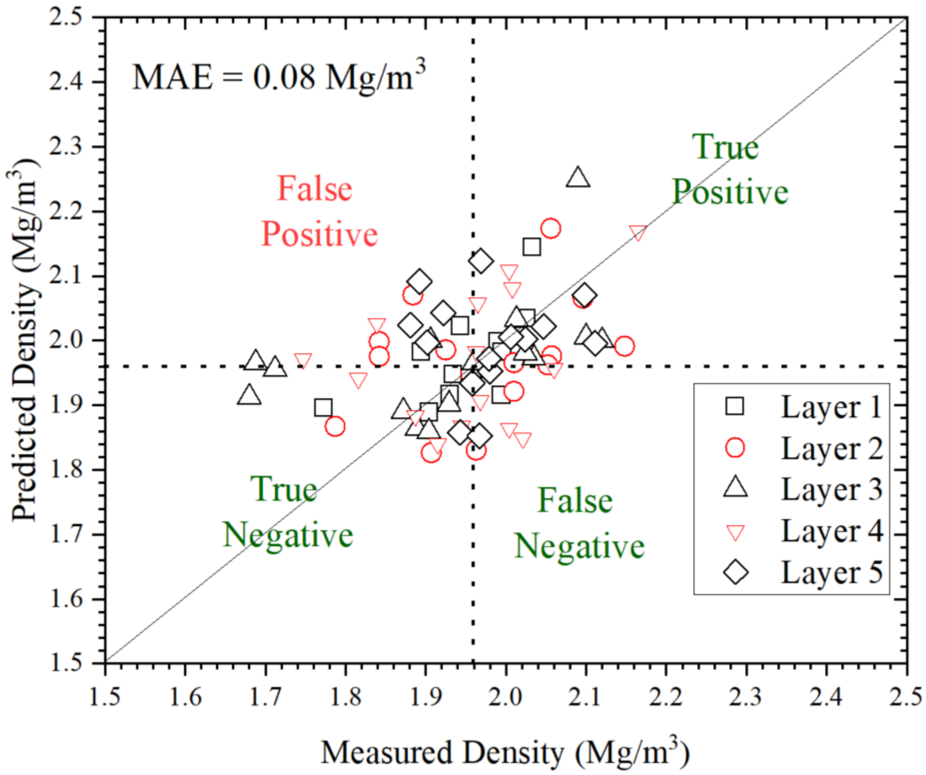

Figure 7: Comparison of predicted dry density using 1-D compaction assumption from the instrumented roller and measured dry density from NDG

For a geotechnical engineer, the most important aspect during compaction is that if the area has been classified correctly so that the action could be taken to improve if needed before placing the next layer on top. The differentiation is done based on the MDD obtained from the standard compaction test 1.96 Mg/m^3 which was around 94% of modified proctor MDD. The prediction is divided into four parts true positive when the predicted and measured are more than MDD, true negative when both the densities are below MDD, false positive when the predicted density is more than MDD but measured density is less than MDD, and false negative is the opposite of false positive. These four together are also known as the confusion matrix of a model. For the 1-D model used, out of 75 data points, the confusion matrix comprised 29,19,15,12 data points for true positive, true negative, false positive and false negative. From the confusion matrix, the prediction accuracy is defined as percentage the method is able to identify true positive and true negative. So, this shows that the prediction accuracy of the 1-D model was 64%, and the error was 36%. However, for a geotechnical site engineer, the percentage of false-positive is the one that should be an issue as this is the problematic area, where the actual density is less but the prediction density is higher. So, the error is now defined as the percentage of prediction in false positive. In this case, it can be seen that the error is 20% only, which shows that the 1-D model can be used to predict the field behaviour with reasonable accuracy as also highlighted in (Tophel *et al.*, 2022). However, the accuracy can be increased if a nonlinear relationship is considered.

The number of data points for the SGD classifier in confusion matrix was 29,25,12,9, respectively, for true positive, true negative, false positive and false negative. The error as described above for the SGD classifier is only 16% which shows a 20% improvement over the 1-D model. The confusion matrix for both the methodology is given in Table 5.

Table 5: Comparison of the predictions of density from the 1-D model and ML model as a confusion matrix

		Predicted Values	
		Positive	Negative
Actual Values	True	29	12
	False	15	19

(a) 1-D model

		Predicted Values	
		Positive	Negative
Actual Values	True	29	09
	False	12	25

(b) ML model

4 CONCLUSIONS

Density, a gravimetric parameter, cannot be measured without taking a sample; hence, most tests are intrusive. Another commonly performed test viz. NDG emits harmful rays, and appropriate certification is needed to operate such a test. Sampling and doing the test is time-consuming and thus seen as a drawback. Therefore, a need for a methodology for the proximal estimation of density in the field arises. The method would allow the contractor or the field practitioner to check compaction quality in real time.

The soil density measurement involves collecting a physical sample and then getting the value by measuring the mass and volume of the sample collected from the field. Density measurement tests take some time and often hinder the contractor who wants to compact another layer of soil as soon as possible because delaying would mean paying extra money for the equipment and labour. This drawback has led researchers and practitioners to develop other QA criteria for estimating the earthwork quality; one of them is modulus-based QA. The modulus-based QA is shown to be quicker than density measurement and thus advocated as superior to density-based QA. The modulus, which is considered to have a unique and direct correlation with density, is considered to replace the density measurement; however, researchers have also found that the correlation between density and modulus is not unique. The correlation also depends on the water content of the sample.

This study proposes a methodology where the density can be measured in real-time by measuring the surface deformation during compaction and then correlating it to the material density. This study was a proof of concept for the proposed methodology. The results showed that measuring the density with very high accuracy is possible. Two models, namely 1-D and ML, were evaluated to estimate the density from measured deformation. It is shown that the nonlinear ML model was superior to the 1-D model by 20%; however, the 1-D model also yielded a satisfactory result. The error in both the models could be attributed to the limitation of the sensor's accuracy, measurement error from NDG and level and staff. In future, the accuracy can be improved by using advanced sensors, more sophisticated analytics and validation through field trials. The suitability of this methodology has been demonstrated for road construction; however, this method can easily be extended to activities involving compaction, such as earthworks in landfills and foundations of buildings and bridges. Performance-based specification necessitates density as a critical parameter, and therefore, this study has a significant application for transforming the current design practice and making present intelligent compaction 'truly' intelligent.

5 REFERENCES

Adam, D. and Kopf, F. (2004) 'Operational Devices for Compaction Optimization and Quality Control (Continuous Compaction Control & Light Falling Weight Device)', in International Seminar on Geotechnic Pavement and Railway Design and Construction, pp. 97–106.

Caicedo, B. (2019) Geotechnics of Roads: Fundamentals. CRC Press, Taylor & Francis Group.

Facas, N. W., Rinehart, R. V. and Mooney, M. A. (2011) 'Development and evaluation of relative compaction specifications using roller-based measurements', Geotechnical Testing Journal, 34(6), pp. 634–642. doi: 10.1520/GTJ102915.

Géron, A. (2017) Hands-on machine learning with Scikit-Learn and TensorFlow : concepts, tools, and techniques to build intelligent systems, O'Reilly Media. O'Reilly Media.

Harris, C. R. et al. (2020) 'Array programming with NumPy', Nature, 585(7825), pp. 357–362. doi: 10.1038/s41586-020-2649-2.

Hu, W. et al. (2020) 'Influence of moisture content on intelligent soil compaction', Automation in Construction. Elsevier, 113(February), p. 103141. doi: 10.1016/j.autcon.2020.103141.

Kodikara, J., Islam, T. and Sounthararajah, A. (2018) 'Review of soil compaction: History and recent developments', Transportation Geotechnics. Elsevier, 17(September), pp. 24–34. doi: 10.1016/j.trgeo.2018.09.006.

Latter, L., Rice, Z. and Andrews, B. (2019) Review of Density Compliance Systems for Subgrade and Embankment Construction - Stage 1, for Main Roads Western Australia.

Lee, J., Lacey, D. and Look, B. (2017) P60: Best practice in compaction QA for pavement and subgrade materials (year 1 – 2016/2017). Available at: www.nacoe.com.au (Accessed: 25 May 2021).

McKinney, W. and others (2010) 'Data structures for statistical computing in python', in Proceedings of the 9th Python in Science Conference, pp. 51–56.

Mooney, M. A. and Rinehart, R. V. (2009) 'In situ soil response to vibratory loading and its relationship to roller-measured soil stiffness', Journal of Geotechnical and Geoenvironmental Engineering, 135(8), pp. 1022–1031. doi: 10.1061/(ASCE)GT.1943-5606.0000046.

Nazzal, M. (2014) Non-nuclear methods for compaction control of unbound materials.

Neyamadpour, A. (2019) '3D electrical resistivity tomography as an aid in investigating gravimetric water content and shear strength parameters', Environmental Earth Sciences. Springer Berlin Heidelberg, 78(19). doi: 10.1007/s12665-019-8603-7.

Pandey, L. M. S., Shukla, S. K. and Habibi, D. (2015) 'Electrical resistivity of sandy soil', Géotechnique Letters, 5(3), pp. 178–185. doi: 10.1680/jgele.15.00066.

Pedregosa, F. et al. (2011) 'Scikit-learn: Machine Learning in Python', Journal of Machine Learning Research, 12, pp. 2825–2830.

Plati, C. and Loizos, A. (2013) 'Estimation of in-situ density and moisture content in HMA pavements based on GPR trace reflection amplitude using different frequencies', Journal of Applied Geophysics. Elsevier B.V., 97, pp. 3–10. doi: 10.1016/j.jappgeo.2013.04.007.

Van Rossum, G. and Drake Jr, F. L. (1995) Python reference manual. Centrum voor Wiskunde en Informatica Amsterdam.

Standards Australia (2002) Soil classification tests— Determination of the soil particle density of combined soil fractions—Vacuum pycnometer method, AS 1289.3.5.2.

Standards Australia (2003) 'AS 1289.5.2.1 — Methods of testing soils for engineering purposes — Method 5.2.1: Soil compaction and density tests — Determination of the dry density / moisture content relation of a soil using modified compactive effort', Methods of testing soils for engineering purposes, pp. 1–13.

Standards Australia (2009) Soil classification tests- Determination of the particle size distribution of a soil—Standard method of analysis by sieving, AS 1289.3.6.1.

Standards Australia (2017) Soil compaction and density tests Determination of the dry density/moisture content relation of a soil using standard compactive effort, AS 1298.5.1.1.

Swileam, G. S. et al. (2019) 'Assessment of soil variability using electrical resistivitytechnique for normalalluvialsoils, Egypt', Plant Archives, 19(1), pp. 905–912.

Tophel, A. et al. (2022) 'Theory-guided machine learning to predict density evolution of sand dynamically compacted under Ko condition', Acta Geotechnica. Springer Berlin Heidelberg. doi: 10.1007/s11440-021-01431-2.

Tophel, A., Kodikara, J. and Walker, J. P. (2021) 'Systems and methods for measuring/estimating geomaterial layer properties due to compaction'. Australia: Patent Cooperation Treaty (PCT) AU2021/051505.

Weber, J. J. (2018) Compaction Testing of Granular Material. South Dakota State University.

Wersäll, C. et al. (2015) 'Frequency variable surface compaction of sand using rotating mass oscillators', Geotechnical Testing Journal, 38(2), pp. 198–207. doi: 10.1520/GTJ20130193.

Wersäll, C. and Larsson, S. (2013) 'Small-scale testing of frequency-dependent compaction of sand using a vertically vibrating plate', Geotechnical Testing Journal, 36(3), pp. 394–403. doi: 10.1520/GTJ20120183.

Yuan, G., Che, A. and Feng, S. (2020) 'Evaluation method for the physical parameter evolutions of highway subgrade soil using electrical measurements', Construction and Building Materials. Elsevier Ltd, 231, p. 117162. doi: 10.1016/j.conbuildmat.2019.117162.

Zargar, M. and Lee, J. (2019) P105: Implementation of Intelligent Compaction Technology in Queensland (Year 1 – 2018/2019) for Asphalt Applications.