Using a Novel Instrumented Roller to Estimate Soil Dry Density During Compaction

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Abstract. Capturing evolution of density or void ratio during the compaction of geomaterials (soils and unbound granular materials) is essential for improved performance. This study developed a framework where the density evolution during compaction can be estimated using advanced instrumentation. The framework's suitability was validated using a simulated large-scale soil box (dimensions: 7.5 m × 4 m × 0.8 m) experiment mimicking the field conditions. Well-graded sand was compacted in 5 layers of 125 mm using a 1.5-tonne mini roller instrumented with Light Detection and Ranging (LiDAR) systems and a total station tracking system for positioning.

The sand's moisture content was homogenised at 8% (w/w) using a concrete truck. The in-situ sampling for measuring density was carried out using Nuclear Density Gauge (NDG) and sand cone test. The data from sensors were collected using a Data Acquisition (DAQ) system connected to a laptop. The measurement of the deformation in real-time provided an opportunity to estimate the density in real-time, and it was estimated using a machine-learning artificial neural network (ANN) model. The estimated density from deformation measured and NDG at the end of compaction shows that estimated density NDG density with an R = 0.9 for one layer, and for other layers, R was more than 0.8. This novel instrumentation allows the density to be measured during compaction with very high accuracy, which has a massive advantage over conventional approaches and contribute to the true Intelligent Compaction (IC) with an advancement of automation in construction.

Keywords: Compaction · Light detection and ranging · Nuclear density gauge · Density · Intelligent compaction

1 Introduction

Compaction of materials (soils and unbound granular materials) in the field are carried out to ensure their superior performance under repeated traffic loads. Density is an

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indicator of compaction. Materials are usually compacted in the field at their Maximum Dry Density (MDD) determined at Optimum Moisture Content (OMC) using Proctor compaction in the laboratory. Achieving the desired MDD in the field is crucial, as under-compacted layers could cause premature failure.

Conventional soil density measurements involve collecting physical samples, measuring the mass and volume of the sample collected, and then calculating the density. This process takes some time and often hinders the contractor who wants to compact another layer of soil as soon as possible because delaying would mean spending extra money for the equipment and labour [1]. The current density measurements are also destructive, and do not cover the entire compacted area. These drawbacks have led researchers and practitioners to develop other QA criteria for estimating the quality of the earthwork; one of them is modulus-based QA [2]. The modulus-based QA is shown to be quicker than density measurement and thus advocated as superior to density-based QA. Modulus, which is considered to have a unique and direct correlation with density, is considered to replace the density measurement; however, researchers have found the correlation between density and modulus is not unique, preferably the correlation also depends on the water content of the sample [3].

One important modulus-based technique is Intelligent Compaction (IC). IC was developed in the 1970s, where the roller drums are fitted with accelerometers, and the acceleration pattern is used to correlate with the degree of soil and asphalt compaction [4–10]. It has already gained popularity in the United States and is accepted as an alternative QA/QC for density measurement.

The IC roller is integrated with temperature, accelerometer, Global Positioning System (GPS) sensors, and a display monitor. The continuous recording of the GPS and accelerometer data provides a user with real-time information about the compaction degree.

The recorded drum response is used to calculate different Intelligent Compaction Measurement Values (ICMVs), which are correlated with density and modulus. The correlation between ICMVs and density is found to be poor; however, the correlation between ICMVs and modulus is found to be suitable for some range of moisture content of material [5, 11]. Recently, the U.S. Department of Transportation (DoT), Federal Highway Administration (FHWA) and The Transtec Group, Inc., a pavement engineering firm, published a technical brief detailing the levels of ICMV (Fig. 1) [12, 13]. At present, the ICMV is developed till around level 3, a real-time estimation of density would mean that there would be a jump from level 3 to level 5 as shown in terms of the development of ICMV.

To solve the issues mentioned above with measuring density accurately, our research established a unique methodology for non-destructively estimating the density of soils and unbound granular materials in real-time during the compaction process. The process comprised employing Light Detection and Ranging (LiDAR) sensors attached to rollers to assess surface deformation and developing an ANN model based on machine learning (ML) to relate the measured parameters to the density.

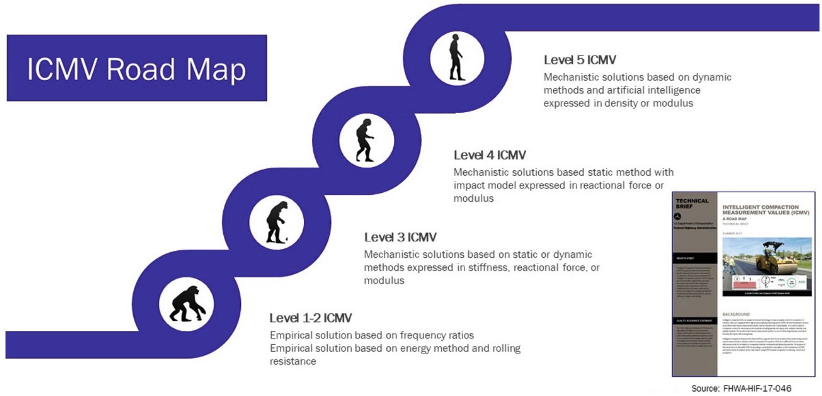

Fig. 1. ICMV roadmap showing the different levels of development associated with IC.

2 Materials and Methods

The test entails compacting multiple layers of material with loose thickness of 125 mm. The material was identified as sand with silty particles, with the remaining Geotechnical parameters provided in Table 1.

Table 1. Geotechnical properties of the material used

Geotechnical property	Value	Standard
Specific gravity (G_S)	2.70	AS 1289.3.5.2 [14]
Median diameter (D_{50}) mm	0.32	AS 1289.3.6.1 [15]
MDD modified Proctor t/m^3	2.08	AS 1289 5.2.1 [16]
OMC modified Proctor (%)	8	AS 1289 5.2.1 [16]
Optimum degree of saturation (S_{ropt}) (%)	70	AS 1289.5.1.1 [17]
Percentage passing the No. 200 sieve	21	AS 1289.3.6.1 [15]
USCS classification	SM	AS 1289.3.6.1 [15]

2.1 Test Bed

The test was conducted in a fabricated soil box with dimensions 7.5 m × 4 m × 0.8 m. The box was custom-made for this study and was kept in an indoor environment to prevent outside influences from influencing the results.

Following steps were undertaken for the entire test:

1. A concrete mixer was used to condition the material to an adequate moisture level (8 per cent w/w).
2. A bobcat was used to load the material into the test setup, then dispersed as uniformly as possible with shovels and rakes (Fig. 2).
3. Before compaction, density measurements were performed with NDG.
4. An optical level and staff was used to map the initial layer thickness.
5. The instrumentation system was double-checked, the signal was zeroed, and the data acquisition system (DAQ) was left on.
6. Next, the material was compacted using the instrumented roller (Fig. 3).
7. The density data from sand cone test was used to determine when compaction was complete. Nuclear Density Gauge (NDG) was used to compare the results with the sand cone apparatus at the end of the compaction process.

Fig. 2. Test site filled with material and levelled before compaction

Fig. 3. Picture of Instrumented roller before compaction

3 Results and Discussion

Using the two LiDAR systems attached in front and back of the front vibrating drum, the deformation was calculated using the diagram shown in Fig. 4.

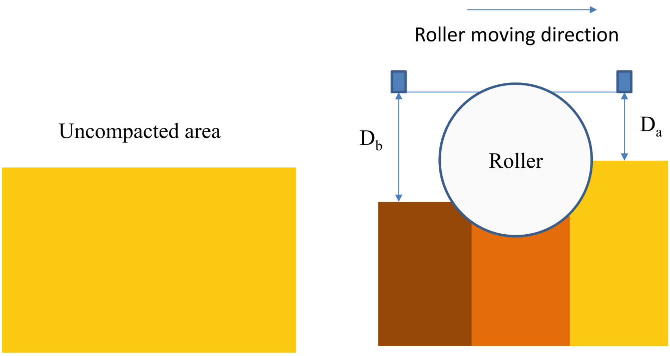

Fig. 4. The methodology to calculate the surface deformation using the two LiDAR, the deformation is calculated as Db - Da.

The surface deformation measured was used to model the density measured from NDG using a 3-layer artificial neural network (ANN) with one input, hidden and output layer as shown in Fig. 5. The input parameters other than surface deformation were initial layer thickness and initial density. Python software and additional packages, including Keras, TensorFlow, Pandas, Numpy, and Seaborn, were used to implement the ANN model [18–23].

The other hyperparameters which includes number of hidden neurons, optimizer and learning rate of the ANN model are listed in Table 2 and were tuned using the Keras tuner [19]. Entire dataset was split into 80% training and 20% testing dataset which was used for validation.

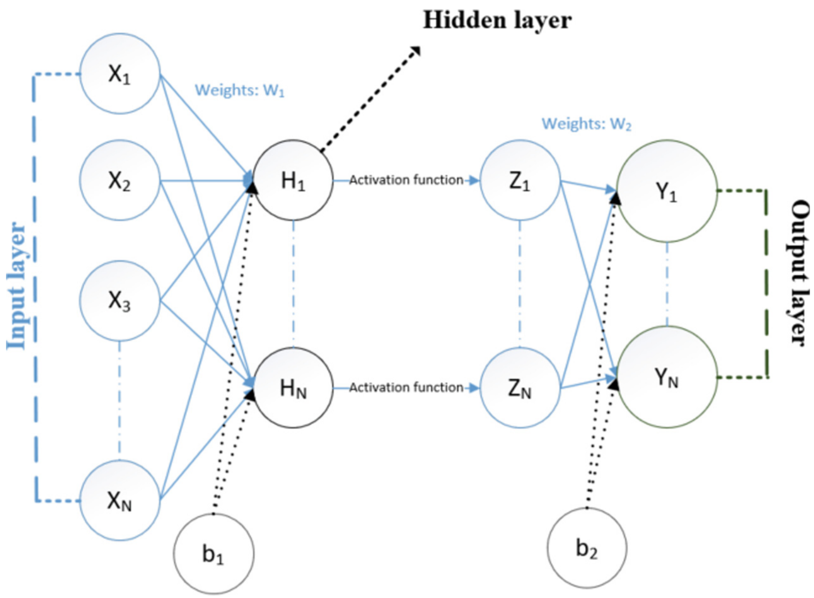

Fig. 5. Structure of the artificial neural network used for this study

The formulation of the ANN can be found below:

$$H = W_1X + b_1, \tag{1}$$

$$Z = F(H), \tag{2}$$

$$Y = W_2Z + b_2, \tag{3}$$

where, X is the input matrix H is the output matrix of the hidden layer, matrix Z is the output after applying the activation function to H, and Y is the prediction from the ANN. W_1 and W_2 are weights between input and hidden layer, between hidden and output layer respectively and constitute the weight matrix W. Similarly, b_1 and b_2 are bias between input and hidden layer, between hidden and output layer respectively and constitute the bias matrix b. F is the activation functions in the hidden layer, which was set to the rectified linear unit (ReLU) [24].

The predicted output Y is then compared to the observed output (Y_{obs}) using the loss function MAE, which has been chosen for this study.

$$\text{Loss function (MAE)} = L(Y_{obs}, Y) = \frac{1}{len(Y)} \sum_{i=1}^{len(Y)} |Y - Y_{obs}|, \tag{4}$$

where, $len(Y)$ represents the length of matrix Y. The loss L is minimised using the back-propagation algorithm by changing the weight matrix W and bias matrix b. The trained model is then used to forecast new data sets after it has been trained.

Table 2. Hyperparameter details of the ANN model developed for this study

Hyperparameter	Value
No. of hidden layers (H)	1
No. of nodes in the hidden layer	3
Optimiser	Adam
Learning rate	0.1

Ten data points were used in each layer for NDG testing. Figure 6 shows the comparison of estimated and measured density using NDG for one layer. The result shows that

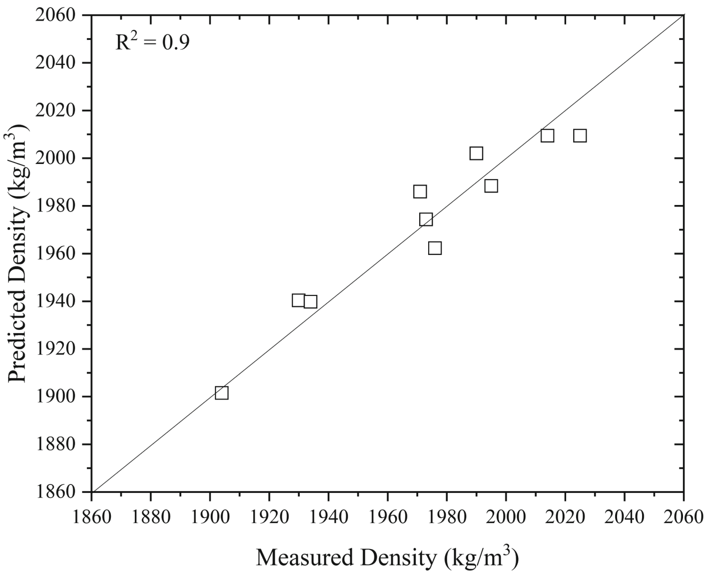

Fig. 6. Comparison between measured and predicted density

the predicted and the measured dataset are related with an R value of 0.9 for this layer. The R value of training and test sets were 0.89 and 0.91 respectively for the layer the comparison of performance of training and testing dataset was used for assessment of generalization of the model. The correlation R between the predicted and the measured dataset of all other layers was more than 0.8.

4 Conclusions

The primary purpose of this work was to explore an alternative method that could provide a better estimation of soil density in the field during compaction. 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. The hypothesis proposed for this study is that if the surface deformation during compaction is captured with the help of a suitable technique, the density can be estimated by correlating the surface deformation with the density.

The surface deformation was measured using two LiDAR systems connected in front and back of the front vibrating drum. The compaction of large areas and the surface deformation measurement using LiDAR will have many data points. ANN model was developed for density prediction, having surface deformation as an input parameter. The result shows that the measured and predicted density correlates with an R^2 of 0.9.

This work could be extended to optimising the operating modes with the input received from the density estimation and therefore transforming the current design practice and contribute significantly in automation in construction. This technology will become a cornerstone in the Industry 4.0 revolution of Intelligent Compaction, which is embodied in Intelligent construction, and will propel it forwards at a quick pace.

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