

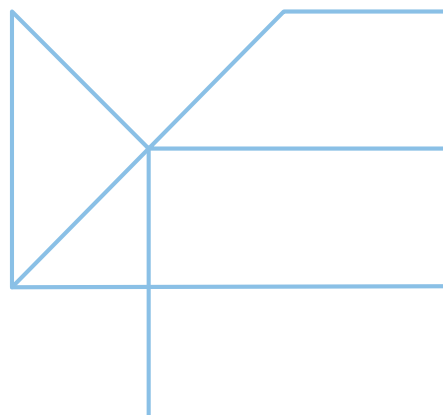
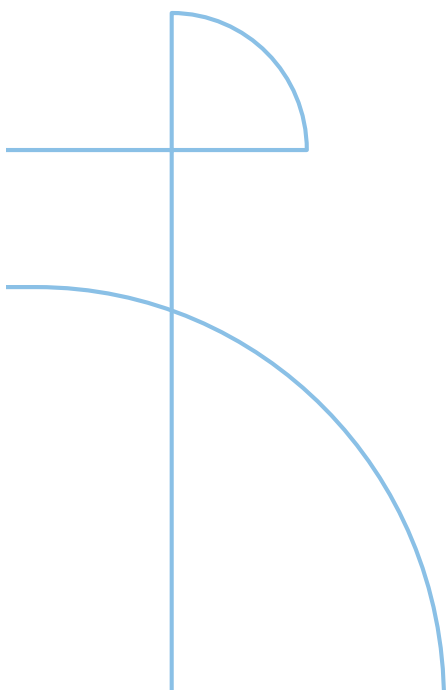


Licentiate Thesis in Civil and Architectural Engineering

Toward reliable vibratory compaction control: Integrating full-scale testing and advanced finite element analysis

WENJUN HUA

KTH ROYAL INSTITUTE OF TECHNOLOGY



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Academic Dissertation which, with due permission of the KTH Royal Institute of Technology, is submitted for public defence for the Degree of Licentiate of Engineering on Friday, the 5th June 2026, at 10:00 AM in Projekthallen, Bygghuset, Brinellvägen 34, KTH Campus.

Licentiate Thesis in Civil and Architectural Engineering
KTH Royal Institute of Technology
Stockholm, Sweden 2026

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TRITA-TRITA-ABE-DLT-2620
ISBN 978-91-8106-647-0

Printed by Universitetsservice US-AB, Sweden 2026

Abstract

Vibratory compaction is widely used for improving the bearing capacity and stiffness of earthworks. The quality of a compacted layer is traditionally verified by spot tests, such as the plate load test (PLT), which provide limited spatial coverage. Continuous compaction control (CCC) addresses this limitation by deriving intelligent compaction measurement values (ICMV) from the roller response. However, the use of CCC for quality assurance is still limited by uncertain correlations between ICMVs and PLT moduli, by incomplete physical interpretation of the roller response, and by the small number of measurements normally available for calibration.

This thesis investigates the reliability of CCC-based quality assurance for vibratory compaction by combining full-scale testing, finite element analysis, and machine learning. Five full-scale trials were conducted at the Dynapac compaction laboratory in Karlskrona on a 1 m thick layer of well-graded gravel. Two single-drum rollers, two PLT plate diameters, and different compaction states were included, and sixteen ICMVs were compared with the deformation modulus from PLTs. A two-dimensional plane-strain finite element model of the roller–soil system was implemented with four constitutive descriptions, ranging from linear elasticity to hypoplasticity with intergranular strain. Finally, six regression algorithms were evaluated on 60 samples in a multi-output framework for estimating E_{v1} and E_{v2} simultaneously.

The full-scale trials show that mechanics-based ICMVs, in particular the loading-phase vibration modulus, provide the strongest correlation with E_{v2} . The 600 mm PLT plate gives stronger and less scattered correlations than the 300 mm plate, and the lighter roller gives stronger correlations than the heavier roller. The numerical study shows that hypoplasticity with intergranular strain gives the most consistent description of cyclic densification, stiffness evolution, and loading–unloading response. It also shows that the influence depth depends on the selected response quantity, with density-related criteria giving larger depths than settlement-based criteria. In the simulations, the vibration modulus is more closely related to the final density state than CMV or OMEGA, while normalized void-ratio reduction helps describe the consumed

part of the available compaction potential. The machine-learning study shows that curated response characteristics improve the prediction of E_{v2} compared with predefined ICMVs. Among the tested algorithms, TabPFN gives the best overall estimates of E_{v2} , while the multi-output framework also enables the E_{v2}/E_{v1} ratio to be estimated. The results demonstrate both the potential and the remaining limitations of CCC-based quality assurance for vibratory compaction.

Keywords

Vibratory compaction, intelligent compaction, continuous compaction control, plate load test, vibration modulus, hypoplasticity, machine learning, quality assurance

Sammanfattning

Vibrationspackning används i stor omfattning för att förbättra bärformågan och styvheten hos jordkonstruktioner. Kvaliteten hos ett packat lager kontrolleras traditionellt med punktvisa försök, till exempel statiska plattbelastningsförsök (PLT), som ger begränsad yttäckning. Yttäckande packningskontroll (eng. *continuous compaction control*, CCC) hanterar denna begränsning genom att härleda intelligenta packningsmätvärden (eng. *intelligent compaction measurement values*, ICMV) från responsen hos en instrumenterad vält. Den praktiska användningen av CCC för kvalitetssäkring begränsas dock fortfarande av osäkra samband mellan ICMV och deformationsmoduler från PLT, av en ofullständig fysikalisk tolkning av vältresponsen och av det begränsade antal mätningar som normalt finns tillgängliga för kalibrering.

I denna avhandling undersöks tillförlitligheten hos CCC-baserad kvalitetssäkring av vibrationspackning genom en kombination av fullskaleförsök, finita elementanalys och maskininlärning. Fem fullskaleförsök utfördes i Dynapacs packningslaboratorium i Karlskrona på ett 1 m tjockt lager av välgraderat grus. Två enkelvalsvältrar, två plattdiametrar för PLT och olika packningstillstånd undersöktes, och sexton ICMV jämfördes med deformationsmodulen från PLT. En tvådimensionell finita elementmodell av systemet vält–jord under plant töjningstillstånd implementerades med fyra konstitutiva modeller, från linjär elasticitet till hypoplasticitet med intergranulär töjning. Slutligen utvärderades sex regressionsalgoritmer på 60 prover i en flermålsformulering för samtidig skattning av E_{v1} och E_{v2} .

Fullskaleförsöken visar att mekanikbaserade ICMV, särskilt vibrationsmodulen under lastfasen, ger starkast korrelation med E_{v2} . PLT-plattan med 600 mm diameter ger starkare och mindre spridda korrelationer än 300 mm-plattan, och den lättare välten ger starkare korrelationer än den tyngre. Den numeriska studien visar att hypoplasticitet med intergranulär töjning ger den mest konsekventa beskrivningen av cyklisk förtätning, styvhetsutveckling och lastnings–avlastningsrespons. Den visar också att influensdjupet beror på vilken responsstorhet som används, där densitetsrelaterade kriterier ger större djup än kriterier baserade på sättning. I simuleringarna har vibra-

tionsmodulen ett tydligare samband med det slutliga densitetstillståndet än CMV eller OMEGA, medan den normaliserade reduktionen av portalet bidrar till att beskriva den utnyttjade delen av den tillgängliga packningspotentialen. Maskininlärningsstudien visar att utvalda responsegenskaper ger bättre prediktion av E_{v2} än fördefinierade ICMV. Bland de testade algoritmerna ger TabPFN de bästa övergripande skattningarna av E_{v2} , medan multi-output-ramverket också gör det möjligt att uppskatta kvoten E_{v2}/E_{v1} . Resultaten visar både möjligheten och de kvarstående begränsningarna med CCC-baserad kvalitetssäkring av vibrationspackning.

Nyckelord

Vibrationspackning, intelligent packningskontroll, yttäckande packningskontroll, plattbelastningsförsök, vibrationsmodul, hypoplasticitet, maskininläring, kvalitets-säkring

Preface

The work presented in this licentiate thesis was carried out at the Division of Soil and Rock Mechanics, Department of Civil and Architectural Engineering, KTH Royal Institute of Technology, between 2024 and 2026. This research was funded by the Swedish Transport Administration through Better Interaction in Geotechnics (BIG) (Grant No. A2023-06) and the Development Fund of the Swedish Construction Industry (SBUF) through Peab Anläggning AB (Grant No. 14198), with additional support from KTH.

I would first like to express my sincere gratitude to my main supervisor, Professor Stefan Larsson, for offering me the opportunity to pursue this work and for his continuous guidance, patience, and trust throughout the project. I am equally grateful to my co-supervisor, Dr. Carl Wersäll of Kerberos Geoteknik AB, whose technical insight, careful reading, and steady encouragement have shaped every part of this thesis.

The full-scale tests that form the experimental backbone of this thesis would not have been possible without the generous support of Dynapac Compaction Equipment AB. I am particularly indebted to Andreas Persson and Fredrik Åkesson for providing access to the compaction laboratory, for their hands-on assistance during the trials, and for many helpful discussions about vibratory roller technology.

I would also like to thank my colleagues at the Division of Soil and Rock Mechanics for the friendly and supportive environment they have created. The discussions in the corridors and around the coffee table have been a constant source of inspiration.

Finally, I would like to thank my family and friends for their companionship and unwavering support throughout this journey.

Wenjun Hua
Stockholm, May 2026

List of appended papers

This licentiate thesis consists of two parts. The first part presents an overview of the research and a summary of the author's contributions. The second part consists of the appended papers.

- Paper A** **Correlating continuous compaction measurement to plate load tests for quality assurance**, *W. Hua, A. Persson, F. Åkesson, C. Wersäll, and S. Larsson. Transportation Geotechnics*, 102157, 2026
- Paper B** **Nonlinear vibration response of a roller–soil system using finite element analysis with hypoplasticity**, *W. Hua, C. Wersäll, and S. Larsson. Manuscript to be submitted*, 2026
- Paper C** **Compaction quality assessment based on machine learning with small datasets**, *W. Hua, C. Wersäll, and S. Larsson. Revised manuscript submitted to the 6th International Conference on Geotechnics for Sustainable Infrastructure Development*, 2026

The author has also contributed to the following publications, which are not appended to this thesis but share the same research context:

- 1. Packningskontroll för framtiden: Modern teknik istället för långsamma försök**
W. Hua, C. Wersäll, and S. Larsson. Bygg & Teknik(1), 24–27, 2025
- 2. Mot tillförlitlig yttäckande packningskontroll – lärdomar från fullskaleförsök**
W. Hua, C. Wersäll, A. Persson, and S. Larsson. In Grundläggningdagen, Stockholmsmässan, Älvsjö, 1–12, 2026
- 3. Utvecklad packningskontroll för framtidens kvalitetssäkring – etapp 1**
W. Hua. SBUF report 14198, Svenska Byggbranschens Utvecklingsfond, 2026

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1 Introduction

1.1 Background

Vibratory compaction is a common ground improvement method in earthwork construction. Granular materials are used as embankment fill and as subbase and base course materials in transport infrastructure such as roads, railways, and airfields. The stiffness achieved during compaction governs the bearing capacity and long-term settlement of the finished structure. Crushed rock is typically used as embankment and base course material in Sweden, and compaction quality is regulated through requirements on the deformation modulus (Swedish Transport Administration 2013).

Single-drum vibratory rollers are the most common equipment for compacting granular fills. A vibratory roller combines the static weight of the drum with a dynamic force generated by rotating eccentric masses. The dynamic force transfers energy to the soil and produces particle rearrangement and densification. The compaction effect depends on the static linear load, vibration frequency, vibration amplitude, travel speed, number of passes, and mechanical properties of the soil. These factors interact in a nonlinear way, which makes the response of the coupled roller–soil system dependent on both operating conditions and material state.

The quality of a compacted layer is traditionally verified by discrete spot tests performed after compaction. Density methods such as the nuclear gauge and the sand cone test measure the dry density and compare it with a reference such as the modified Proctor density. Modulus methods such as the plate load test (PLT) and the light weight deflectometer measure the stiffness of the compacted layer. The PLT is the prescribed reference method (Swedish Transport Administration 2014a): the first and second loading cycles give the deformation moduli E_{v1} and E_{v2} , and the ratio E_{v2}/E_{v1} is used as a measure of the residual compaction potential. Spot tests are time-consuming, labor-intensive, and spatially sparse. Only a small fraction of the compacted surface is tested, and under-compacted zones between measurement points can remain unde-

tected.

Continuous compaction control (CCC), also referred to as intelligent compaction (IC), was developed to overcome these limitations by moving the measurement from the soil surface to the roller itself. In the late 1970s, Forssblad and Thurner independently instrumented vibratory rollers with drum-mounted accelerometers and showed that the vibration signal carries information about the stiffness of the soil beneath the drum (Forssblad 1980; Thurner, and Sandström 1980). Since then, the principle has developed into a measurement system in which the accelerometer output is processed in real time to produce an intelligent compaction measurement value (ICMV). The ICMV is displayed to the roller operator and tagged with a global positioning system (GPS) position to build a compaction map of the work site, as shown in Figure 1.1.1. Compared with spot testing, CCC provides full areal coverage and immediate feedback during compaction, reducing the risk of under-compaction and over-compaction.

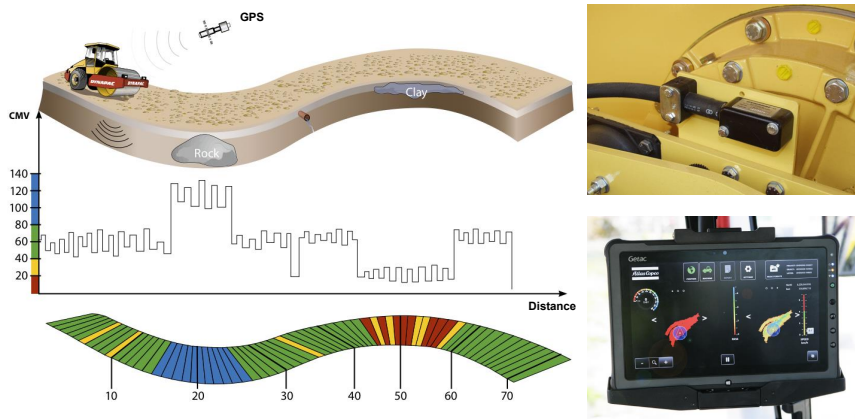


Figure 1.1.1: Schematic of the CCC measurement chain. An accelerometer mounted on the roller records the drum vibration; the signal is processed in real time by an on-board computer to produce an ICMV, which is combined with the GPS position to build a compaction map of the work site.

A large number of ICMVs have been proposed, each derived from a different aspect of the roller response. These values are usually grouped into acceleration-based, mechanics-based, and energy-based indicators. Empirical indicators such as the compaction meter value (CMV) are widely implemented in commercial rollers. However, CCC has not been universally accepted as a formal, standalone method for compaction quality assurance.

For CCC to be directly used in quality assurance, the roller measurement must be related to an accepted measure of compaction quality. This relation remains uncertain. Field studies on granular soils have shown that the ICMV–modulus correlation depends on the soil type, roller, operating conditions, and reference test method (White, and Thompson 2008; Pistol, Hager, and Adam 2021; Pistol, Hager, Kopf, et al. 2025). One practical source of uncertainty is the reference test itself. In the PLT, the plate diameter affects the stressed soil volume and therefore the measured deformation mod-

ulus. The roller also has its own excitation characteristics and influence depth. The combined effect of PLT plate diameter and roller type has not been examined systematically in full-scale test conditions.

The interpretation of ICMVs is also limited by the nonlinear character of the drum–soil interaction. During vibratory compaction, the soil stiffness changes with stress level, strain amplitude, and compaction state. The compaction performance of granular materials under vibratory rollers has been studied at KTH in the last decade, with particular attention to the operating frequency (Wersäll 2013; Wersäll 2016; Wersäll, Nordfelt, et al. 2017; Wersäll, Nordfelt, et al. 2018). However, validated numerical models that can reproduce cyclic densification and the evolution of ICMVs remain rare (Kennally et al. 2015; Paulmichl et al. 2020).

Data-driven methods provide another way to relate roller measurements to conventional quality acceptance tests. By combining several ICMVs and vibration response features, such methods can account for nonlinear relations that are difficult to describe with a single indicator. Their use in compaction quality assurance is nevertheless limited by the small datasets normally available from field testing, which makes overfitting a major concern.

This thesis addresses these issues through full-scale tests, numerical modeling, and machine learning (ML). The full-scale tests provide paired ICMV and PLT measurements for two rollers, two plate diameters, and several compaction states. A plane-strain finite element method (FEM) model is used to examine the drum–soil interaction and the simulated ICMV response. A small-sample ML study investigates the estimation of deformation moduli from multivariate roller measurements.

1.2 Objectives

The overall aim of this thesis is to improve the reliability with which vibratory compaction of granular soils can be assessed for quality assurance purposes. Three specific objectives are pursued:

1. To quantify the correlation between a representative set of ICMVs and the deformation modulus from the PLT in controlled full-scale tests, and to assess how this correlation depends on the PLT plate diameter and on the choice of vibratory roller (Paper A).
2. To develop a plane-strain finite element model of the roller–soil interaction, and to evaluate the level of constitutive fidelity required to reproduce the nonlinear dynamic response and the evolution of the simulated ICMVs during vibratory compaction (Paper B).
3. To examine whether multivariate ML models can improve the estimation of E_{v1} and E_{v2} from roller measurements under small-dataset conditions, and to identify the features that most strongly influence the estimates (Paper C).

1.3 Outline of thesis

This thesis consists of an introductory part and three appended papers. The introductory part is intended as a summary and complement to the appended papers.

Chapter 2 describes the full-scale vibratory compaction trials and the correlation analysis between ICMVs and the PLT deformation modulus. This chapter corresponds to Paper A.

Chapter 3 presents the plane-strain FEM model and compares four constitutive models of increasing complexity. This chapter corresponds to Paper B.

Chapter 4 presents the ML study, in which six regression algorithms are compared using two feature sets. This chapter corresponds to Paper C.

Chapter 5 summarizes the three appended papers. Chapter 6 presents the conclusions and outlines directions for future work.

2 Full-scale tests

This chapter presents the experimental component of the thesis. A series of full-scale vibratory compaction trials was carried out to evaluate the correlation between a broad set of ICMVs and the deformation modulus from the PLT under controlled conditions, and to investigate how this correlation is affected by the choice of PLT plate and by the roller used. A complete description of the tests, together with extended analyses and discussion, is given in Paper A.

2.1 Experimental program

2.1.1 Test site and material

Five full-scale trials were conducted at the compaction laboratory of Dynapac Compaction Equipment AB in Karlskrona, Sweden, as shown in Figure 2.1.1. The test bed is a bottomless tank, 27 m by 7 m, bounded by vertical concrete walls, with a 1 m thick layer of compacted material underlain by a well-compacted rockfill that has been in place for over forty years. The test surface was positioned at the center of the tank and divided into two adjacent lanes, each 22 m long and 2.13 m wide, matching the drum width of the rollers. For Trials 3–5, each lane was further subdivided into three areas separated by 2 m buffers, so that different numbers of roller passes could be applied on the same lane. The two test layouts are shown in Figure 2.1.2.

At the beginning of each trial, the soil was loosened to a depth of about 0.7 m with an excavator and manually graded. After a preparatory static pass, the PLT measurement locations were marked on the surface with spray paint. The test area was then subjected to a specified number of vibratory passes (N), followed by two static passes at the same speed of 1 m/s. Compaction was carried out by alternating between the two lanes every two consecutive passes. Within each lane, the roller traveled back and forth, so that odd- and even-numbered passes represent forward and backward rolling, respectively,

with each trip counting as one pass. After conditioning overnight for about 24 hours, PLTs were conducted at the marked locations along the lane centerline. The same preparation and conditioning protocol was applied across all trials. The marked PLT locations on the compacted surface are shown in Figure 2.1.3.

The test material was a well-graded gravel (GW), a common embankment fill material in Sweden, consisting of crushed rock with a coefficient of uniformity $C_u = 107$, coefficient of curvature $C_c = 1.5$, specific gravity $G_s = 2.7$, and a maximum dry density of 2230 kg/m^3 from the modified Proctor test. The maximum particle size was 32 mm. The gradation fell within the grading envelope for base course materials in compacted road layers (Swedish Transport Administration 2013), determined in accordance with (Swedish Transport Administration 2014b). The moisture content was controlled at approximately 3%, corresponding to the natural moisture content (NMC), and was well below the optimum moisture content (OMC) of about 6%. The test bed was covered with tarpaulins between operations to prevent evaporation, and sampling at the beginning and end of each trial confirmed that the moisture content was maintained within a narrow range.

2.1.2 Vibratory rollers and instrumentation

Two Dynapac single-drum vibratory rollers were used: a CA3500D and a CA6500D. The CA6500D was selected to represent a heavy-duty roller with high compaction capability, while the CA3500D represents a lighter and more common model with approximately half the static linear load, at 36 kg/cm and 65 kg/cm, respectively. Both rollers were operated exclusively at their high-amplitude settings and at a fixed vibration frequency of 24 Hz. The frequency was kept below the maximum of the two rollers as a precaution against double-jumping, a phenomenon in which the drum intermittently loses contact with the ground as the compacted material stiffens and re-impacts only every second excitation cycle, which introduces noise and instability in the acceleration signals. The complete set of operating parameters of the two rollers is reported in Paper A.

The measurement system consisted of a biaxial accelerometer mounted on the roller drum, an eccentric position sensor, a hand-held trigger, a data acquisition system, and an on-board computer. The vertical and horizontal accelerations of the drum were recorded during compaction. The eccentric position sensor provided the angular position of the rotating shaft and was used to determine the phase lag between the eccentric force and the measured acceleration. Each time the drum passed over a marked PLT spot, the trigger was pressed manually to generate a pulse signal, which was used to locate the spot in the recorded signal. All channels were sampled at 2 kHz and transferred to a personal computer for subsequent analysis.

2.1.3 Plate load test

PLTs were performed in accordance with the Swedish standard (Swedish Transport Administration 2014a). A normal stress is applied to a circular loading plate in incre-



Figure 2.1.1: Test bed and roller in operation at the indoor laboratory.

ments over two loading cycles, and the corresponding settlement is measured with a displacement transducer. The deformation modulus from the second cycle E_{v2} is used to represent ground stiffness, and the ratio E_{v2}/E_{v1} between the second and first cycles is considered a measure of the residual compaction potential. The roller used in each trial also served as the counterweight for the PLT loading.

Two plate diameters were used: a standard 300 mm plate and a larger 600 mm plate, as shown in Figure 2.1.4. The maximum applied stresses for the first loading cycle were 500 kPa for the 300 mm plate and 250 kPa for the 600 mm plate. For the reloading cycle, these values were 450 kPa and 200 kPa, respectively. The use of two plate sizes was motivated by the knowledge gap concerning how plate size affects the correlation between PLT results and ICMVs, since the plate size governs the measurement depth of the PLT and therefore the soil volume that contributes to E_{v2} .

2.1.4 Intelligent compaction measurement values

Raw accelerometer data recorded during compaction were used to compute sixteen ICMVs covering the three main categories reported in the literature: acceleration-based, mechanics-based, and energy-based indicators. The indicators, grouped by category, are summarized below. Detailed formulations can be found in Paper A and in the references listed there.

Acceleration-based ICMVs are derived from the time-domain or frequency-domain characteristics of the vertical acceleration signal. Time-domain indicators include the crest factor (CF) (Hua, Yang, et al. 2018; Chen, Hu, et al. 2022). Frequency-domain indicators are defined as amplitude ratios of different harmonic components of the signal. The CMV (Thurner, and Sandström 1980) was first proposed and re-

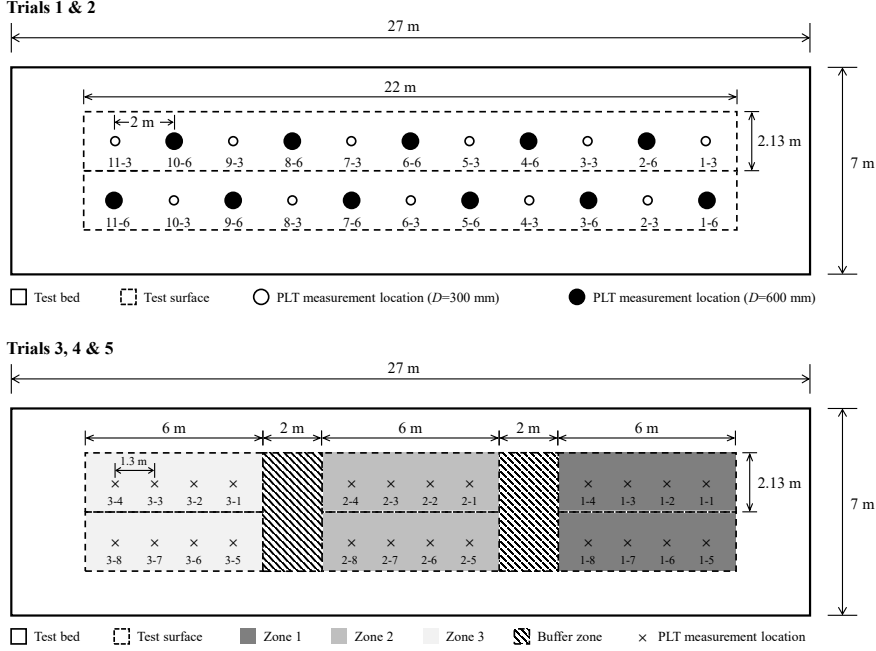


Figure 2.1.2: Test layouts for different trials.

mains the most widely used. Variants such as acceleration intelligent compaction value (AICV) (Ma et al. 2022), compaction control value (CCV) (Scherocman et al. 2007), total harmonic distortion (THD) (Mooney, Gorman, et al. 2005), and the turbulence factor F_t (Furuya, and Fujiyama 2011) also consider the influence of higher-order harmonic and sub-harmonic components, and F_t additionally includes a normalized ratio between the ground contact force and the front module weight.

Mechanics-based ICMVs are derived from the force–displacement hysteresis of the drum during a vibration cycle and are physically more closely related to the mechanical properties of the compacted material. Representative indicators include the roller-integrated stiffness k_s (Anderegg, and Kaufmann 2004), the vibration modulus E_{vib} (Pistol, and Adam 2018; Pistol, Hager, Kopf, et al. 2025), and the vibration compaction value (VCV) (Zhang et al. 2015). The hysteresis curve can be further analyzed to distinguish between the loading and unloading phases within a vibration cycle. The stiffness and modulus during the loading phase are denoted k_1 and $E_{\text{vib}1}$, and during the unloading phase k_2 and $E_{\text{vib}2}$. The values for the entire cycle are denoted k_b and E_{vib} .

Energy-based ICMVs interpret compaction as an energy transfer process from the roller to the ground. OMEGA (Brandl, and Adam 1999) is defined as the area of the force–displacement hysteresis loop, and machine drive power (MDP) (Thompson, and White 2008) represents the propulsion energy required to overcome rolling resistance.



Figure 2.1.3: Compacted surface with marked PLT measurement locations before further testing.

More recent indicators include dissipation measured value (DMV) (Wu 2021; Wu et al. 2022) and compaction energy value (CEV) (Ye et al. 2020; Yang et al. 2022; Dan et al. 2024), both derived from advanced signal analysis. The compaction power per unit volume E (Liu et al. 2016) represents the total compaction work exerted on a unit volume of material for a given number of passes.

In total, sixteen ICMVs were computed and analyzed in Paper A: CMV, AICV, CCV, THD, F_t , and CF (acceleration-based); k_1 , k_2 , k_b , E_{vib1} , E_{vib2} , and E_{vib} (mechanics-based); and DMV, CEV, OMEGA, and E (energy-based).

2.1.5 Test matrix

Table 2.1.1 summarizes the five trials. Across the five trials, a total of 116 PLTs were conducted. In Trials 1 and 2, PLTs with the two plate diameters (300 and 600 mm) were alternated after six vibratory passes, with measurement points spaced 2 m apart along the rolling direction. Six passes were selected to ensure satisfactory compaction quality while avoiding over-compaction. This configuration isolates the influence of plate diameter on the PLT measurement and its correlation with the ICMVs.

Trials 4 and 5 were designed to cover a wider range of compaction states. In each trial, the three areas of the test lane received $N = 2, 4$, and 8 vibratory passes, respectively, yielding eight PLT measurements with the 600 mm plate for each N . The lower bound of two passes was chosen because it produced more stable readings than a single pass, and a single pass also carries the risk of premature test termination due to excessive settlement. Trial 3 was used to evaluate the effect of the two additional static passes following vibratory compaction, which address the surface loosening commonly ob-

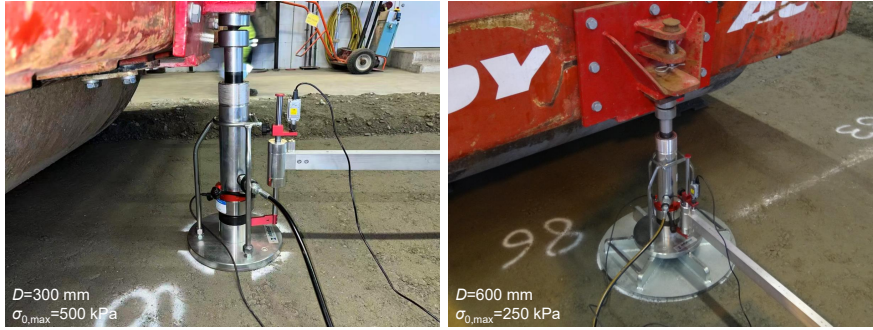


Figure 2.1.4: Plate load test setup with the 300 mm and 600 mm circular loading plates.

served at the end of vibratory compaction. In Trials 3–5, only the 600 mm plate was used, and the measurement spacing was reduced to 1.3 m to obtain a sufficient number of data points while maintaining a reasonable distance between adjacent measurement locations.

Table 2.1.1: Summary of the test setups. Comma-separated values of N denote the number of vibratory passes applied to each of the three areas in that trial.

Trial No.	D (mm)	Roller	N
1	300, 600	CA6500D	6
2	300, 600	CA3500D	6
3	600	CA6500D	8, 6 [†] , 6
4	600	CA3500D	8, 4, 2
5	600	CA6500D	8, 4, 2

[†] PLTs were performed after six vibratory passes without the additional static compaction.

2.2 Measurement results

2.2.1 Plate load test results

The mean E_{v1} values from the 300 mm and 600 mm plates differed by less than 2% and were independent of the plate diameter, confirming uniform initial soil conditions across the test areas. However, the larger plate produced mean E_{v2} values that were 5–7% lower than the smaller plate, a statistically significant difference. The reduction is attributed to two factors: the lower peak stress applied to the larger plate produces less soil hardening, and its greater measurement depth averages stiffness over deeper and less stiff soil layers. The 600 mm plate also showed a slightly lower coefficient of variation (CV) in E_{v2} .

Both rollers produced very similar mean E_{v1} values (relative difference below 2%), confirming consistent initial conditions across the trials. The heavier CA6500D produced mean E_{v2} values that were 7–10% higher than those of the CA3500D, in line with its greater static weight and ground contact force. Its consistently lower CV indicates better compaction uniformity due to a larger and deeper influence zone.

The effect of the number of passes was investigated in Trials 4 and 5 with the 600 mm plate and $N = 2, 4$, and 8, with the results shown in Figure 2.2.5. For both rollers, additional passes increased E_{v1} and E_{v2} and reduced E_{v2}/E_{v1} . The CA6500D reached nearly the same stiffness at $N = 2$ and $N = 4$ as the CA3500D did at $N = 4$ and $N = 8$, confirming its higher compaction capability. For both rollers the mean values increased only slightly between $N = 4$ and $N = 6$, which supports the selection of six passes as a stable reference condition for comparing plate diameters. The CA6500D generally provided better uniformity up to $N = 6$, but at $N = 8$ the standard deviation of E_{v2} increased markedly and the mean E_{v2} barely increased further. This suggests that excessive compaction energy begins to disturb the aggregate structure and reduce uniformity, an effect that is more pronounced for the heavier roller. The surface loosening that accompanies this phenomenon was the motivation for the additional static passes applied at the end of each trial. A separate comparison between different areas in Trial 3 showed that the additional static compaction increased the mean E_{v1} and E_{v2} values by 66.5% and 16.7%, respectively.

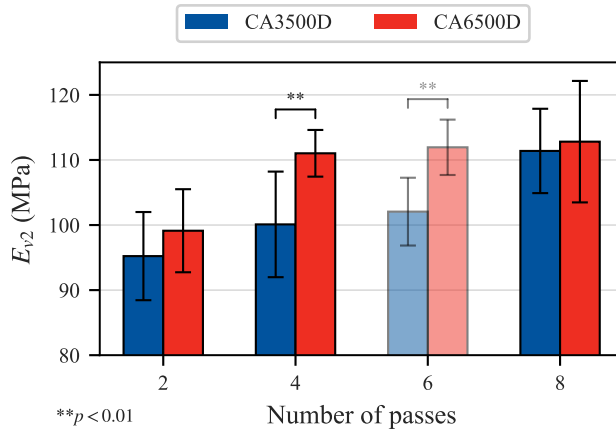


Figure 2.2.5: Variation of E_{v2} measured with the 600 mm plate as a function of N . Bars show mean values and error bars denote the standard deviation.

2.2.2 Interrelationships among ICMVs

Descriptive statistics computed over all trials and passes show that the sixteen ICMVs span very different dynamic ranges and variabilities. The CF has the narrowest range and the lowest variability, which limits its discriminative resolution. CEV, DMV,

OMEGA, k_2 , and $E_{\text{vib}2}$ maintain a narrow to moderate range and are relatively stable. Harmonic-based ICMVs (CMV, AICV, THD, CCV) and the other stiffness-based ICMVs (k_b , k_1 , E_{vib} , $E_{\text{vib}1}$) display wider ranges with greater variability, while F_t and E exhibit the broadest ranges and the highest variability.

The interrelationships among ICMVs were examined through hierarchical clustering based on Spearman correlation coefficients (r) and through principal component analysis (PCA), as shown in Figure 2.2.6. Most indicators are strongly and positively correlated ($r > 0.8$, $p < 0.01$), except CF and DMV, which behave as outliers. The remaining indicators fall into three distinct clusters:

- Cluster 1: E , F_t , CMV, THD, CCV, and AICV. This cluster groups together acceleration-based indicators, mixed with E as a process-level descriptor.
- Cluster 2: CEV, k_b , E_{vib} , k_1 , and $E_{\text{vib}1}$. This cluster is associated with the loading phase of the drum–soil interaction.
- Cluster 3: OMEGA, k_2 , and $E_{\text{vib}2}$. This cluster is associated with the unloading phase of the drum–soil interaction.

The first two principal components of the PCA explain 73% of the total variance and place the three clusters in distinct quadrants, confirming the clustering. The first component separates acceleration-related information from stiffness- and energy-related information, while the second component differentiates loading and unloading behavior. Within each cluster, the intra-cluster correlations are high ($\bar{r}_{\text{intra}} = 0.92\text{--}0.98$) and the inter-cluster correlations are also high ($\bar{r}_{\text{inter}} = 0.80\text{--}0.88$), indicating strong redundancy inside clusters and substantial overlap across them. On this basis, CMV, $E_{\text{vib}1}$, and $E_{\text{vib}2}$ were selected as representative indicators for the three clusters, and CEV, OMEGA, and E were retained as energy-based indicators with more distinct behavior.

2.2.3 Correlations between ICMVs and the deformation modulus

For the comparison between plate sizes, linear regressions between E_{v2} and the representative ICMVs were fitted to 22 paired measurements at $N = 6$ from Trials 1 and 2, as shown in Figure 2.2.7. For the 300 mm plate the coefficient of determination (R^2) remained at or below 0.3 for all the selected ICMVs, while the 600 mm plate consistently yielded higher values in the range 0.3–0.5. The improvement is attributed to the greater measurement depth of the larger plate, which better matches the influence depth of the rollers, attenuates the contribution of stiffer near-surface layers, and averages out local inhomogeneities. The relatively similar regression slopes of $E_{\text{vib}1}$ and $E_{\text{vib}2}$ across plate sizes suggest that mechanics-based indicators offer a more consistent correlation with E_{v2} that is less sensitive to plate diameter than acceleration-based indicators. The 600 mm plate is therefore preferable for calibration when feasible.

For the comparison between rollers, the ICMV– E_{v2} correlations were computed on the combined data set from Trials 4 and 5, which covers three compaction states ($N = 2, 4$, and 8) with the 600 mm plate, as shown in Figure 2.2.8. Pooling the three compaction states gives a wide and representative range of E_{v2} values, which makes the regression more robust. The overall ranking of the three ICMV categories was mechanics-based

($R^2 = 0.4\text{--}0.7$) $\geq$ acceleration-based ($R^2 = 0.4\text{--}0.6$) $>$ energy-based ($R^2 = 0.2\text{--}0.5$), with a few individual exceptions. The poorest correlations were observed for DMV and CF: DMV yielded $R^2 \approx 0$ and is therefore unsuitable as an indicator of ground stiffness, while CF is limited by its narrow range. ICMVs derived from the same principles, such as the harmonic family (CMV, AICV, CCV, THD) and the stiffness family (k and E_{vib}), showed nearly identical scatter patterns.

Within the stiffness family, E_{vib1} (and equivalently k_1) had the strongest correlation with E_{v2} , followed by E_{vib} (k_b) and E_{vib2} (k_2). This indicates that the loading phase of the drum–soil interaction better reflects E_{v2} , which is itself a loading stiffness. Acceleration-based indicators that include more harmonic and sub-harmonic components, such as THD and F_t , tended to correlate slightly better than CMV, and F_t reached correlations similar to those of the mechanics-based indicators because it also includes a ground contact force term. Among the energy-based indicators, CEV and OMEGA formed two distinct clusters corresponding to the two rollers, and the relatively weak correlation of OMEGA is likely related to partial contact loss (Adam, and Kopf 2004), which intensifies as the soil stiffens. The indicator E increases almost linearly with the number of passes, whereas E_{v2} grows nonlinearly and eventually levels off, which weakens their correlation over a wide range of N .

Compared with the CA6500D, the lighter CA3500D produced stronger correlations and larger regression slopes for nearly all ICMVs, indicating a higher sensitivity of the roller response to changes in E_{v2} . The best correlation across all combinations was obtained for E_{vib1} with the CA3500D, with a correlation coefficient R of about 0.8. The superior performance of the lighter roller is attributed to reduced contact loss during vibratory loading and to a better match between its influence depth and the measurement depth of the 600 mm PLT plate. The heavier CA6500D introduced more variability in the response, as reflected in the wider error bands observed in the evolution of the ICMVs with N , which weakens its correlation with E_{v2} .

Taken together, the measurement results indicate that mechanics-based ICMVs, and in particular the vibration modulus during the loading phase, are the most suitable indicators for correlating CCC measurements with the PLT deformation modulus under the tested conditions. Acceleration-based indicators such as the CMV family offer a comparable correlation with a less direct link to soil stiffness. Energy-based indicators are conceptually appealing but perform less well because the theoretical compaction energy differs from the energy actually absorbed by the soil. The results also show that ICMV– E_{v2} correlations remain strongly dependent on the roller used, and that machine-specific calibration is still necessary in the current CCC practice. These findings motivate the numerical study in Chapter 3 of the roller–soil interaction and the data-driven modeling study in Chapter 4.

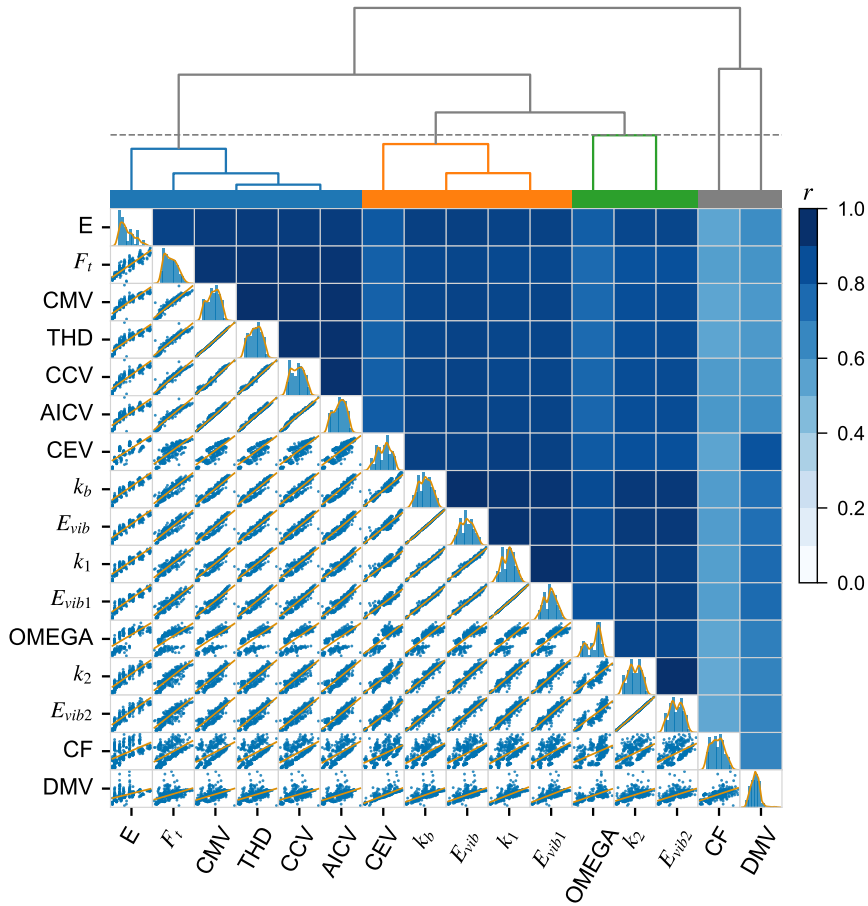


Figure 2.2.6: Hierarchically clustered correlation matrix for the sixteen ICMVs. The color scale shows the r between pairs of indicators.

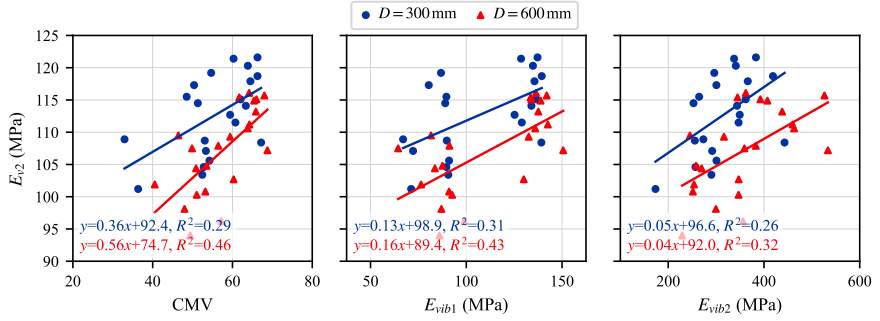


Figure 2.2.7: Correlation between E_{v2} measured with the 300 mm and 600 mm plates and representative ICMVs at $N = 6$.

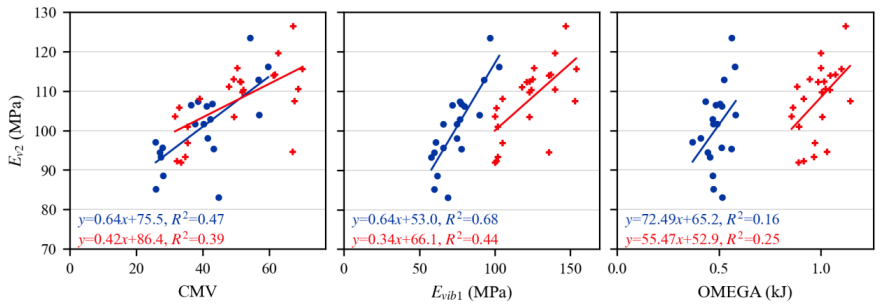


Figure 2.2.8: Correlation between E_{v2} measured with the 600 mm plate and different ICMVs for the two rollers, using the combined data from Trials 4 and 5 at $N = 2, 4$, and 8.

3 Finite element analysis

The results reported in Chapter 2 show that the correlations between ICMVs and deformation modulus are not uniformly strong and remain machine-dependent. Their physical interpretation is also limited by the nonlinear nature of the drum–soil interaction. The roller response depends on soil state, roller properties, operating parameters, and the evolving contact between the drum and the ground. A numerical model that can reproduce both the vibration response and the progressive densification of the soil is therefore useful for interpreting measured ICMVs and for conducting parametric studies that would be impractical in the field. This chapter summarizes the two-dimensional dynamic FEM model developed in Paper B and the main findings from the comparison of four soil constitutive models.

3.1 Numerical framework

3.1.1 Overview

The model is formulated under a plane-strain assumption, with the model thickness equal to the drum width. Only in-plane responses are considered, since the vibration primarily occurs in the vertical direction. Experimental observations have shown that plane-strain conditions extend to a depth of about 0.5 m beneath the drum center (Mooney, and Rinehart 2009), and numerical studies have confirmed that a plane-strain model provides a sufficiently accurate assessment of the compaction effect (Paulmichl et al. 2020).

The model includes the soil medium and the vibratory roller. The roller is represented by a vibrating drum, a frame mass, and a vertical spring–dashpot isolation system between the drum and the frame. The simulation is designed to account for the repeated moving load, evolving drum–soil contact, and irreversible soil densification during a continuous roller pass.

3.1.2 Soil domain and constitutive models

The subgrade is modeled as a homogeneous, isotropic half-space of well-graded gravel, consistent with the material used in the full-scale tests of Chapter 2. The region of interest is a rectangular finite domain with a length of 12 m and a depth of 4 m. At the lateral and bottom boundaries, 4 m infinite elements (Lysmer, and Kuhlemeyer 1969) are attached to absorb propagating waves and reduce reflections. The material behavior in the infinite elements is linear elastic.

Four constitutive descriptions of gravel are compared:

1. **Linear elastic:** a baseline model used to isolate the influence of stiffness on the dynamic response.
2. **Mohr–Coulomb (MC) plasticity:** a frictional model with pressure-dependent shear strength and a non-associated flow rule.
3. **Modified Drucker–Prager/Cap (DPC) plasticity:** a pressure-dependent plasticity model with a Drucker–Prager shear failure surface and an elliptical cap for hydrostatic compression.
4. **Hypoplasticity with intergranular strain (Hypo+IGS):** a state-dependent model in which stiffness and dilatancy–contractancy evolve with stress level and void ratio (Von Wolfersdorff 1996; Niemunis, and Herle 1997). The intergranular strain extension captures recent strain history, small-strain stiffness, and cyclic hysteresis. A detailed description of the constitutive law is given by Mašín (2019).

The reference comparison uses $E = 40$ MPa for the linear elastic, MC, and DPC models, a cap eccentricity of $R = 0.5$ for the DPC model, and an initial relative density of $D_{r0} = 50\%$ for Hypo+IGS. Additional simulations were performed with six elastic modulus levels, $E = 10, 20, 40, 60, 80,$ and 100 MPa, for the elastic, MC, and DPC models. For the DPC model, three cap eccentricities, $R = 0.3, 0.5,$ and $0.7,$ were also considered. For Hypo+IGS, nine initial void ratios were prescribed, corresponding to $D_{r0} = 10\%$ to 90% in increments of 10% . Because the four models were not calibrated against a single common laboratory dataset, the comparison is used for qualitative and mechanistic interpretation rather than direct quantitative ranking.

The Hypo+IGS parameters were adopted from the Hochstetten gravel (Herle, and Gudehus 1999). Table 3.1.1 summarizes the basic hypoplastic parameters used in the reference case. A small apparent cohesion of 5 kN/m^2 was added to prevent numerical instabilities from tensile stresses near the free surface, and a thin elastic “protective foil” was applied to the first row of soil elements. The complete parameter set for all four constitutive models is given in Paper B.

3.1.3 Vibratory roller

Both rollers used in the full-scale tests, CA3500D and CA6500D, are represented in the numerical model. The drum is modeled as an analytical rigid body, and the corresponding drum and frame masses are assigned to reference points at the drum center

Table 3.1.1: Basic hypoplastic parameters used for the Hypo+IGS model: critical-state friction angle φ_c , granulate hardness h_s , pressure exponent n , reference void ratios e_{d0} , e_{c0} , e_{i0} at zero pressure, and density exponents α and β .

φ_c (°)	h_s (GPa)	n (–)	e_{d0} (–)	e_{c0} (–)	e_{i0} (–)	α (–)	β (–)
36	32	0.18	0.26	0.45	0.50	0.10	1.9

and the front frame. The isolation system between the drum and the frame is represented by an equivalent vertical spring–dashpot element, as shown in Figure 3.1.1. The roller parameters, including drum mass, frame mass, eccentric moment, isolation stiffness, and isolation damping, are taken from the manufacturer data used in Paper B.

The drum–soil interaction is modeled using surface-to-surface contact with finite sliding. Tangential behavior follows a Coulomb friction law with $\mu = 0.3$, and the normal behavior follows a hard-contact formulation that permits separation between the drum and the soil. Both rollers are operated at a vibration frequency of 24 Hz and a travel speed of 1 m/s, matching the full-scale test conditions.

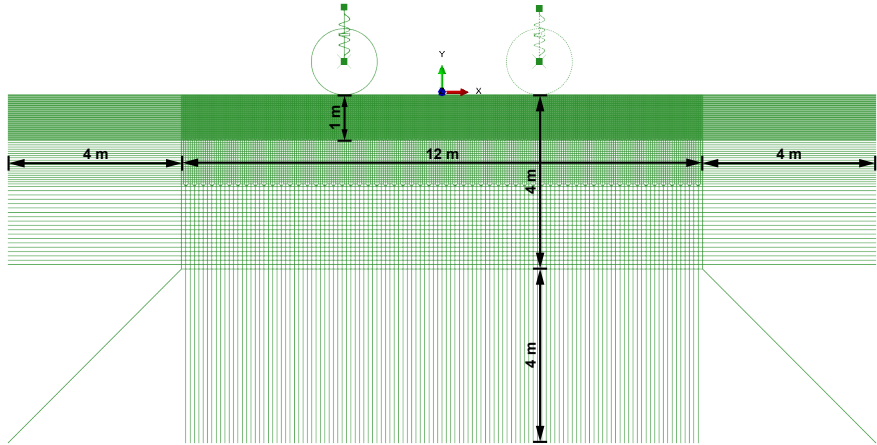


Figure 3.1.1: Sketch of the plane-strain FEM model showing the soil domain, infinite element boundaries, and the roller represented as a rigid drum with lumped frame mass and spring–dashpot isolation system.

3.1.4 Analysis steps and discretization

The analysis is carried out in five steps. First, an in-situ stress state is established through a K_0 procedure. Gravity is then applied to equilibrate the initial stress state. The drum is seated by a prescribed 5 mm downward displacement, and the static axle load is applied. In the dynamic compaction step, horizontal motion is imposed at the

target speed of 1 m/s and a downward sinusoidal excitation force is applied at the drum center. The travel speed and excitation force are ramped over an acceleration period of 0.5 s to reduce impact-induced numerical oscillations.

The soil domain is discretized using four-node bilinear plane-strain quadrilateral elements. The mesh is refined to $0.025 \text{ m} \times 0.025 \text{ m}$ in the upper 1 m of soil, coarsens to $0.05 \text{ m} \times 0.05 \text{ m}$ between depths of 1 and 2 m, and coarsens further to $0.1 \text{ m} \times 0.1 \text{ m}$ between depths of 2 and 4 m. The mesh resolves up to the fifth harmonic of the operating frequency ($f_{\max} = 120 \text{ Hz}$) and includes at least ten elements across the approximate 0.3 m drum–soil contact width (Pistol, Hager, Kopf, et al. 2025). The final model contains 27 404 elements.

The dynamic boundary-value problem is solved implicitly in ABAQUS/Standard R2025 using the Hilber–Hughes–Taylor time-integration scheme with the numerical damping parameter $\alpha = -1/3$. The maximum time increment is $\Delta t_{\max} = 2 \times 10^{-4} \text{ s}$, giving more than 200 time steps per vibration cycle. Rayleigh damping is used as a numerical viscous damping contribution; the material hysteresis and frictional dissipation arise from the constitutive models and the contact formulation. With Hypo+IGS, simulating one roller pass from $x = -2.25 \text{ m}$ to $x = 2.0 \text{ m}$ over 4.5 s requires approximately seven days on one AMD EPYC 7742 cluster core.

3.2 Simulation results

3.2.1 Surface settlement

The static axle load produces a localized and nearly symmetric settlement zone beneath the drum. During vibratory compaction, the settlement field becomes asymmetric. A settlement trough develops mainly below and behind the drum, while an upward displacement zone, or bow wave, appears in front of the drum. This response shows that the vibration-induced deformation cannot be represented by the static axle load alone, as shown in Figure 3.2.2.

The four constitutive models predict different deformation patterns. The elastic model recovers most of the deformation after unloading and therefore cannot represent permanent settlement. The MC and DPC models produce residual deformation after yielding, but their response depends strongly on their plastic flow rules and hardening assumptions. Hypo+IGS gives the most consistent representation of the progressive deformation caused by repeated loading and unloading.

3.2.2 Stress, strain, and densification

The stress response attenuates with depth for all constitutive models. For the Hypo+IGS reference case, the peak vertical stress decreases from about -187 kPa at a depth of 0.125 m to about -64 kPa at a depth of 1 m. The stress histories are also asymmetric with respect to the drum position, which reflects the phase shift between the moving load and the soil response.

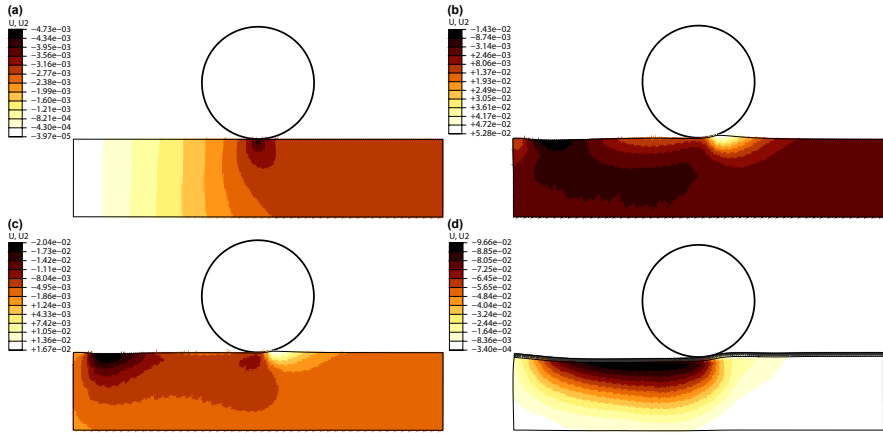


Figure 3.2.2: Simulated surface deformation and vertical displacement contours when the vibrating drum passes the reference section for the (a) Elastic, (b) MC, (c) DPC, and (d) Hypo+IGS models.

The strain response is more sensitive to the constitutive model than the stress response. The MC model mainly produces shear-induced dilation in the upper layer. The DPC model produces a narrow contractive zone through the cap mechanism, but the contraction is limited and surrounded by a larger shallow zone of dilative volumetric plastic strain. Hypo+IGS predicts persistent contractive volumetric strain at all investigated depths and captures cumulative densification.

The density evolution in the Hypo+IGS simulations depends on both the initial soil state and the roller type. Loose and medium-dense initial states show a clear relative void-ratio reduction over a substantial part of the upper layer. For the CA3500D roller, the maximum relative void-ratio reduction is about 0.3 for $D_{r0} = 10\%$ and about 0.2 for $D_{r0} = 50\%$. The heavier CA6500D roller distributes the compaction effect to greater depths, while the lighter CA3500D roller produces its largest reduction mainly in the upper 0.5–1.0 m, as shown in Figure 3.2.3.

3.2.3 Influence depth

The depth of influence depends on the response quantity used to define it. In Paper B, the influence depth is defined as the deepest depth at which the change from the pre-compaction state remains above 10% of its peak value. The criterion is applied separately to displacement, strain, void ratio, and relative void-ratio measures.

Table 3.2.2 shows that displacement-based influence depths are the shallowest, ranging from about 1.0 to 1.3 m. Strain-based influence depths are larger, about 1.4 to 2.0 m. Density-based influence depths are larger still, about 1.5 to 2.4 m. The heavier roller generally produces a larger influence depth than the lighter roller, and the influence depth tends to increase with D_{r0} , especially for strain- and density-based cri-

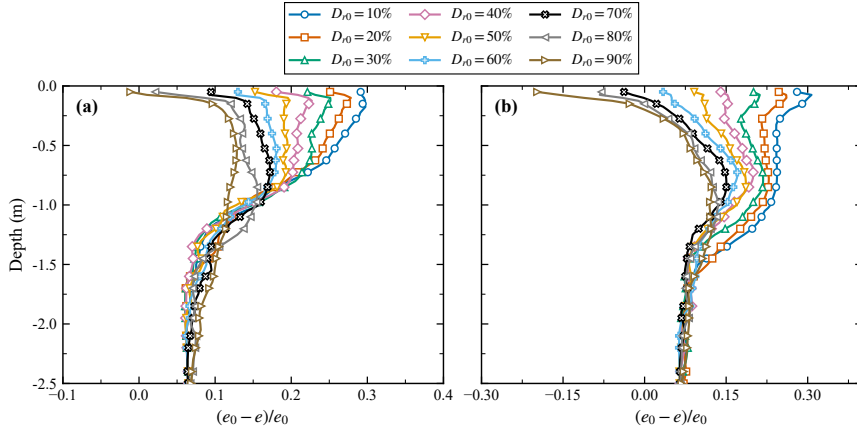


Figure 3.2.3: Relative void-ratio reduction profiles after compaction for different initial relative densities and roller types: (a) CA3500D and (b) CA6500D.

teria. These results show that settlement influence and densification influence should be treated as separate quantities when roller-integrated measurements are compared with depth-averaged or composite spot-test results. The effective measurement depth of the spot test should therefore be checked against the compaction influence depth.

Table 3.2.2: Influence depths determined from different response-based criteria, in m.

Quantity	Roller	$D_{r0} = 20\%$	$D_{r0} = 50\%$	$D_{r0} = 80\%$
u_2	CA3500D	1.02	1.03	1.27
	CA6500D	1.24	1.25	1.29
ε_{yy}	CA3500D	1.43	1.54	1.73
	CA6500D	1.55	1.64	2.02
e	CA3500D	1.50	1.60	2.19
	CA6500D	1.65	1.94	2.39
$(1 + e_d)/(1 + e)$	CA3500D	1.49	1.59	2.18
	CA6500D	1.64	1.93	2.39

3.2.4 Intelligent compaction measurement values

For the CA3500D roller simulated with Hypo+IGS, the acceleration response shows clear components at the operating frequency and at the second harmonic. The CMV response is nonlinear over the investigated density range. It remains about 3–4 for $D_{r0} = 10\%$ – 60% and then increases rapidly for denser states, reaching about 17 at

$D_{r0} = 90\%$. This indicates that CMV is especially sensitive to stronger contact nonlinearity and harmonic distortion in dense states.

The force–displacement loops become steeper as the initial density increases, and the peak contact force increases most clearly for $D_{r0} = 80\%$ and 90% . The vibration modulus during loading, E_{vib1} , increases from about 13 MPa at $D_{r0} = 10\%$ to about 47 MPa at $D_{r0} = 90\%$. The unloading modulus, E_{vib2} , increases from about 45 MPa to about 126 MPa over the same range and remains consistently larger than E_{vib1} . This separation reflects the path-dependent response of the drum–soil system. OMEGA follows the same general trend, increasing from about 193 J to about 328 J, but its increase is most pronounced at higher densities, as shown in Figure 3.2.4.

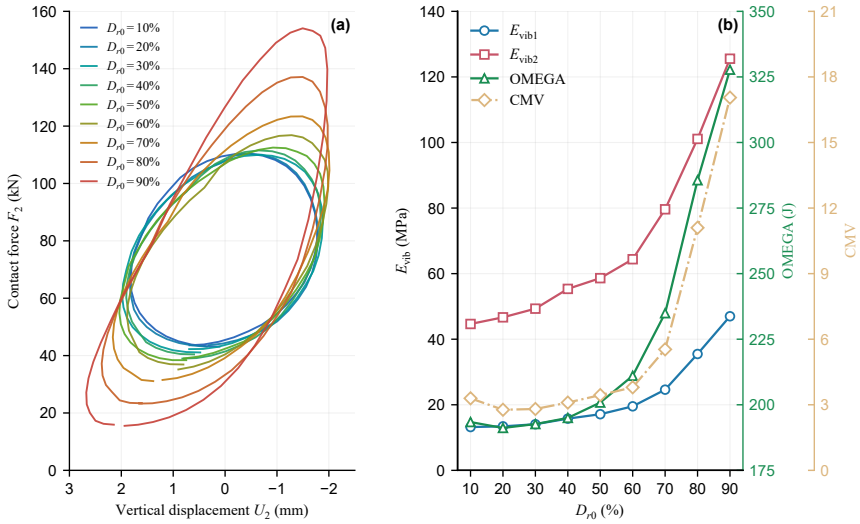


Figure 3.2.4: Contact force–displacement response and average E_{vib1} , E_{vib2} , OMEGA, and CMV values for different initial relative densities.

3.2.5 Relationship between ICMV and density state

The simulated ICMVs were compared with depth-averaged density-related state variables over averaging depths of 1.0, 1.5, and 2.0 m. The results show that E_{vib1} and E_{vib2} are more closely related to the final density state than CMV or OMEGA. This is consistent with the physical meaning of the vibration modulus, which is derived from the contact force–displacement response and therefore reflects the dynamic stiffness of the compacted ground.

The correlation with incremental void-ratio reduction is weaker and more sensitive to the selected averaging depth. This is because a loose soil can experience a large density increase while still remaining relatively soft after one pass, whereas a dense soil

may show only a small additional density increase but produce a high dynamic stiffness. When the void-ratio reduction is normalized by the initially available compaction potential, the relationship with the ICMV becomes clearer, with R^2 values up to 0.97 for the CA350D roller. The results therefore indicate that ICMVs should primarily be interpreted as indicators of the current compacted state, while normalized compaction potential can help describe the remaining densification capacity, as shown in Figure 3.2.5.

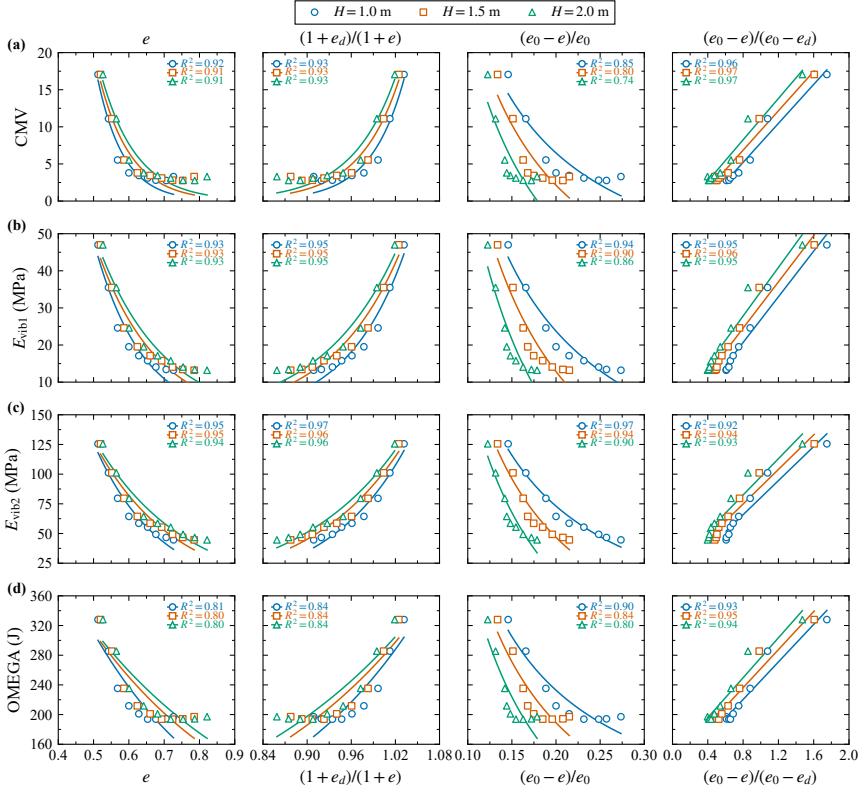


Figure 3.2.5: Relationships between depth-averaged density-related quantities and ICMVs.

3.2.6 Role of the constitutive model

The comparison of the four models highlights the importance of the soil constitutive description. A linear elastic model may be useful for preliminary studies of wave propagation or the response of already compacted ground, but it cannot predict permanent settlement. The MC model introduces shear yielding, but it is insufficient when the objective is to predict densification. The DPC model is more appropriate when com-

pression plasticity and cap hardening are important, but in the present simulations its contractive zone is limited and it does not fully reproduce path-dependent stiffness.

Hypo+IGS provides the most complete description for the present problem because it couples stress level, void ratio, recent strain history, and small-strain stiffness. It directly updates the density state and captures contractive volumetric response, stiffness evolution, and separate loading and unloading behavior. This makes it suitable for simulating cyclic densification, residual compaction potential, and roller-integrated measurements that depend on the loading–unloading path. The cost is a higher demand on calibration, numerical stability, and computational time.

4 Data-driven models

As presented in Chapter 2, the overall linear correlations between individual ICMVs and E_{v2} are generally not strong. Although simple linear regression remains the most commonly used and practically implementable approach, it may fail to accurately capture the inherently nonlinear relationship between soil stiffness and roller response in certain situations, such as at higher compaction levels. Furthermore, despite the significant redundancy among existing ICMVs, different categories of indicators exhibit a certain degree of complementarity. A multivariate and nonlinear approach, particularly ML, should therefore improve the estimation of the deformation modulus. It is also important to examine whether selected response characteristics derived from the measured drum motion and the contact force–displacement curves retain information that is not fully represented by predefined ICMV formulas. This chapter describes a ML workflow that uses multi-output regression to estimate both E_{v1} and E_{v2} simultaneously from roller-measured quantities, and evaluates the feasibility of estimating the E_{v2}/E_{v1} ratio continuously. A complete description of the study, including all algorithmic details and supplementary results, is given in Paper C.

4.1 Machine learning workflow

4.1.1 Data preparation

The data were drawn from the same full-scale trials described in Chapter 2. Of the 116 PLTs performed across the trials, 60 measurements obtained with the same plate diameter and under consistent soil conditions were retained for the ML study. The 60 samples were partitioned into a training set (80%, 48 samples) and a test set (20%, 12 samples). Both E_{v1} and E_{v2} were treated as simultaneous targets in a multi-output regression formulation, which preserves the correlation between the two moduli and allows the E_{v2}/E_{v1} ratio to be computed directly from the estimated moduli.

4.1.2 Feature extraction

Two feature sets were constructed to evaluate different representations of the drum–soil interaction. Feature Set 1 consisted of selected ICMVs, while Feature Set 2 consisted of curated vibration response characteristics extracted from acceleration signals and contact force–displacement curves.

Feature Set 1 (selected ICMVs): Starting from the sixteen ICMVs computed in Chapter 2, a compact set was selected to retain representative information while reducing redundancy. ICMVs with low Spearman correlation coefficients with E_{v2} were excluded. The final set contained five selected ICMVs from three categories: F_t , CEV, E_{vib1} , E_{vib2} , and OMEGA. Together, these features represent harmonic amplitude, ground stiffness, and energy transfer.

Feature Set 2 (curated response characteristics): Instead of relying on pre-defined ICMV formulas, eight response characteristics were extracted from the measured drum acceleration and the contact force–displacement response. The final set consisted of A_1 , A_2 , v_{max} , z_d , k_1 , k_2 , $E_{loading}$, and $E_{unloading}$. These variables describe acceleration, velocity, displacement, loading and unloading stiffness, and the energy transmitted to and returned from the soil. This strategy is intended to preserve more of the measured drum–soil response than the fixed mathematical formulations of existing ICMVs.

4.1.3 Algorithms

Six regression algorithms were evaluated to represent different modeling approaches:

1. **Multiple linear regression (MLR):** a linear baseline used to determine whether more complex, nonlinear algorithms provide a measurable benefit.
2. **Random forest (RF)** (Breiman 2001): a tree-based ensemble method that builds multiple independent decision trees and averages their estimates. It is generally robust to noise.
3. **Extreme gradient boosting (XGBoost)** (Chen, and Guestrin 2016): an advanced tree-based ensemble that builds decision trees sequentially, where each new tree corrects the errors of all previous ones. It includes built-in regularization to prevent overfitting.
4. **Support vector regression (SVR)** (Smola, and Schölkopf 2004): a kernel-based method that maps input features into a higher-dimensional space to handle nonlinearity. The radial basis function kernel was used in this study.
5. **k -Nearest neighbors (KNN)** (Cover, and Hart 1967): a distance-based method that estimates the target by averaging the values of the k most similar historical samples in the dataset.
6. **TabPFN** (Hollmann et al. 2025): a modern deep-learning foundation model for tabular data. It is pre-trained on millions of synthetic datasets and performs inference without requiring any task-specific hyperparameter tuning.

This makes it suitable for small datasets, where standard cross-validation tuning procedures can overfit the data.

Bayesian hyperparameter optimization with 15 iterations and 5-fold cross-validation was applied to RF, XGBoost, SVR, and KNN. MLR and TabPFN were fitted without hyperparameter search. Repeated 5-fold cross-validation with 10 repeats was also performed on the training set to assess stability.

4.1.4 Evaluation and interpretability

Model performance was assessed on the test set using R^2 and root mean square error (RMSE). Metrics were reported separately for E_{v1} and E_{v2} . The E_{v2}/E_{v1} ratio was computed from the predicted moduli and evaluated using RMSE. To interpret the model estimates, Shapley additive explanations (SHAP) values (Lundberg, and Lee 2017) were computed for the primary target, E_{v2} . SHAP decomposes each model output into additive feature contributions grounded in cooperative game theory, providing a locally faithful measure of how much each input feature drives the output.

4.2 Evaluation results

4.2.1 Predictive performance

Table 4.2.1 summarizes the test performance of all six algorithms on both feature sets, and Figure 4.2.1 shows the same comparison graphically. On Feature Set 1, SVR achieved the highest test R^2 for E_{v2} , with $R^2 = 0.34$ and RMSE = 7.1 MPa. On Feature Set 2, TabPFN achieved the highest accuracy for E_{v2} , with $R^2 = 0.45$ and RMSE = 6.5 MPa. The corresponding measured versus estimated moduli on the test set are shown in Figure 4.2.2.

MLR generally performed poorly on the test set, including negative R^2 values for E_{v1} in both feature sets. This confirms that the relationship between roller response and soil stiffness is nonlinear and cannot be accurately captured by a simple linear combination of input variables. RF and XGBoost showed strong training performance, but their lower test performance indicates that tree-based models remain sensitive to overfitting when the available dataset is small. SVR generalized more consistently because its regularized formulation limits model complexity while still allowing nonlinear relationships through the kernel. TabPFN showed stable performance for the primary E_{v2} target without hyperparameter tuning, but its weak E_{v1} estimates indicate that this stability did not translate into balanced multi-output generalization.

The poorer test performance for E_{v1} indicates that this target is more sensitive to local variability and less reliably inferred from the roller response alone. The deformation moduli used as target values should also not be regarded as exact ground truth, because they inherit uncertainty from the PLT procedure. In addition, the low and sometimes negative R^2 values should be interpreted in light of the limited test-set size, where a

Table 4.2.1: Test performance of the six algorithms on Feature Set 1 and Feature Set 2. Bold values indicate the best E_{v2} result for each feature set and the lowest RMSE for the E_{v2}/E_{v1} ratio.

Set	Model	E_{v2}		E_{v1}		E_{v2}/E_{v1}
		R^2	RMSE (MPa)	R^2	RMSE (MPa)	RMSE
1	MLR	-0.01	8.8	-0.71	5.7	0.36
1	RF	0.29	7.4	-0.02	4.4	0.34
1	XGBoost	0.15	8.1	-0.12	4.6	0.36
1	SVR	0.34	7.1	-0.28	4.9	0.35
1	KNN	0.13	8.2	-0.55	5.4	0.38
1	TabPFN	0.28	7.5	-0.91	6.0	0.41
2	MLR	0.29	7.4	-0.73	5.7	0.38
2	RF	0.34	7.1	0.10	4.1	0.35
2	XGBoost	0.28	7.5	0.03	4.3	0.37
2	SVR	0.32	7.2	0.04	4.3	0.34
2	KNN	0.29	7.4	-0.34	5.0	0.38
2	TabPFN	0.45	6.5	-0.97	6.1	0.43

small number of individual prediction errors can strongly affect the calculated statistics.

4.2.2 Feature-set comparison and E_{v2}/E_{v1} estimation

Figure 4.2.3 compares the best test performance obtained for each target and feature set. For both E_{v1} and E_{v2} , the best result was obtained with Feature Set 2. This shows that preserving relatively raw response characteristics helps the algorithms map the roller response to soil stiffness more effectively than relying only on predefined ICMVs. The improvement was clearest for E_{v2} : the best result increased from $R^2 = 0.34$ with SVR on Feature Set 1 to $R^2 = 0.45$ with TabPFN on Feature Set 2.

The simultaneous estimation of E_{v1} and E_{v2} also makes it possible to compute the E_{v2}/E_{v1} ratio directly from the model outputs. For the E_{v2}/E_{v1} ratio, the lowest RMSE was 0.34, obtained by SVR on Feature Set 2. RF gave a similar RMSE on Feature Set 2 (RMSE = 0.35) and the lowest RMSE on Feature Set 1. These results indicate that the preferred algorithm depends on the intended use: TabPFN is attractive for practical quality assurance (QA) when E_{v2} is the primary design-relevant target, whereas RF or SVR may be better suited for balanced multi-output prediction or for estimating the residual compaction potential through E_{v2}/E_{v1} . Because the ratio depends directly on the less accurately estimated E_{v1} , it should be interpreted as a decision-support quantity rather than a replacement for PLTs.



Figure 4.2.1: Comparison of test performance for the six algorithms on Feature Set 1 and Feature Set 2.

4.2.3 Feature importance

SHAP values were computed to identify the features that most strongly drive the E_{v2} estimates. Table 4.2.2 summarizes the feature importance ranking for Feature Set 2 across the nonlinear models. The second-harmonic acceleration amplitude A_2 was the most consistently top-ranked feature, while the loading stiffness k_1 , the unloading stiffness k_2 , and the displacement amplitude z_d also ranked among the most influential features.

Table 4.2.2: Feature importance ranking for E_{v2} prediction using Feature Set 2, based on mean absolute SHAP values.

Rank	RF	XGBoost	SVR	KNN	TabPFN
1	A_2	A_2	A_2	A_2	A_2
2	E_{loading}	k_2	k_1	k_1	k_1
3	k_2	z_d	z_d	k_2	z_d
4	k_1	k_1	k_2	z_d	v_{max}
5	z_d	$E_{\text{unloading}}$	A_1	A_1	E_{loading}
6	$E_{\text{unloading}}$	E_{loading}	$E_{\text{unloading}}$	$E_{\text{unloading}}$	k_2
7	v_{max}	A_1	E_{loading}	E_{loading}	$E_{\text{unloading}}$
8	A_1	v_{max}	v_{max}	v_{max}	A_1

The SHAP summary plot for TabPFN is shown in Figure 4.2.4. The features A_2 , k_1 , z_d , and v_{max} showed wide ranges of contributions. Higher values of A_2 , k_1 , z_d , k_2 , and $E_{\text{unloading}}$ generally contributed positively to the E_{v2} estimate, whereas higher values of v_{max} , E_{loading} , and A_1 generally contributed negatively. This pattern is physically

reasonable: stronger harmonic response, higher stiffness, larger vibration amplitudes, and greater energy return to the drum are expected when compacting stiffer ground.

The two distinct clusters observed for $v_{\max}$ and E_{loading} likely reflect the different compaction capabilities of the two rollers. Larger A_1 values may correspond to response regimes in which an increased fundamental component is linked to a lower predicted E_{v2} after the effects of higher-ranking features such as A_2 have been accounted for. The rankings of k_1 and E_{loading} compared with those of k_2 and $E_{\text{unloading}}$ further indicate that the loading branch provides more informative features for E_{v2} prediction than the unloading branch, although the unloading stiffness k_2 remains important in several models.

Taken together, the results show that nonlinear ML algorithms can estimate E_{v2} from roller-measured quantities with moderate accuracy even when the training set is small. Curated response characteristics outperform predefined ICMVs, and the most influential features have a clear physical link to harmonic amplitude, ground stiffness, and drum displacement. The multi-output formulation also enables estimation of the remaining compaction potential, although the accuracy of the E_{v2}/E_{v1} ratio is limited by the uncertainty in the E_{v1} prediction. These findings indicate that data-driven stiffness estimation may complement the bivariate ICMV–PLT correlation analysis of Chapter 2.

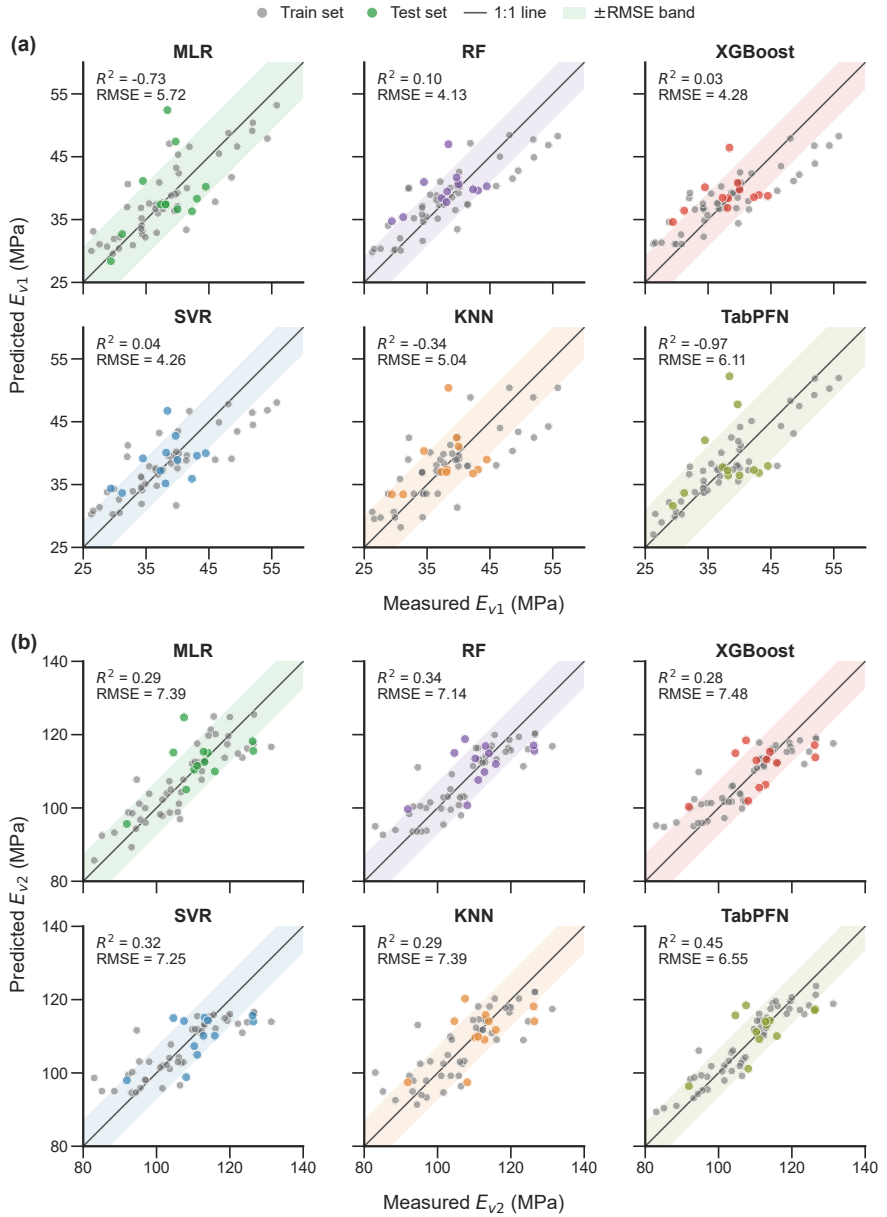


Figure 4.2.2: Measured versus estimated deformation moduli for the six algorithms on the test set using Feature Set 2.

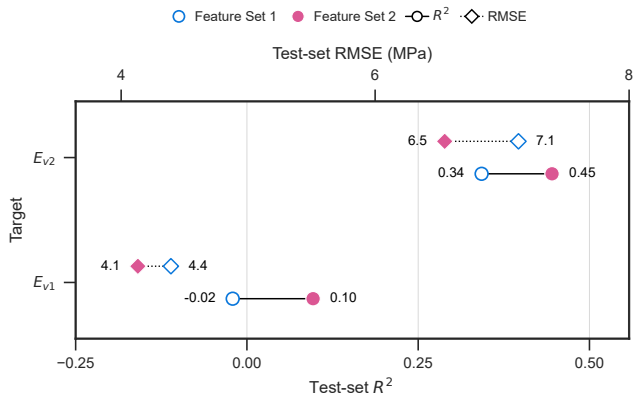


Figure 4.2.3: Target-wise comparison of the best test performance for Feature Set 1 and Feature Set 2.

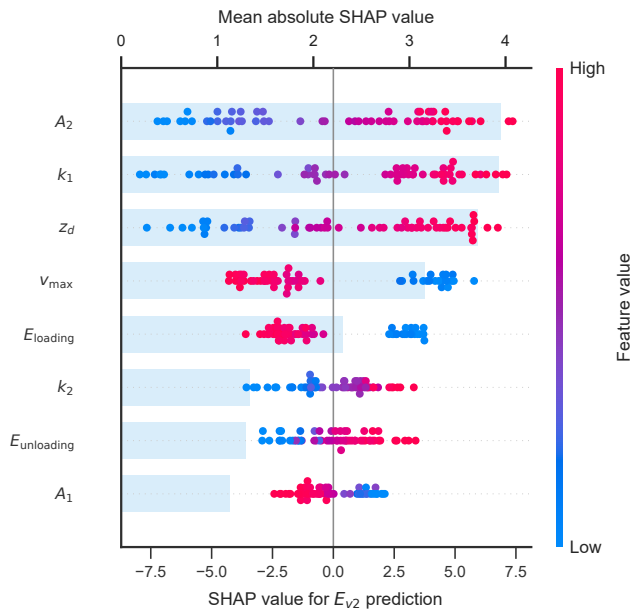


Figure 4.2.4: SHAP summary plot showing feature contributions to the TabPFN estimate of E_{V2} using Feature Set 2.

5 Summary of appended papers

5.1 Paper A

Correlating continuous compaction measurement to plate load tests for quality assurance

Wenjun Hua, Andreas Persson, Fredrik Åkesson, Carl Wersäll, and Stefan Larsson
Published in *Transportation Geotechnics*, 102157, 2026.

The paper presents results from five full-scale vibratory compaction trials carried out on a 1 m thick well-graded gravel layer at natural moisture content. Two single-drum vibratory rollers were used, with static linear loads of approximately 35 and 65 kg/cm. Both rollers were operated at a fixed vibration frequency of 24 Hz and high amplitude. Two PLT plate diameters (300 mm and 600 mm) and three compaction states ($N = 2, 4$, and 8 vibratory passes) were tested. Sixteen ICMVs covering acceleration-, mechanics-, and energy-based families were computed from the recorded drum accelerations. Their interrelationships were examined through hierarchical clustering and PCA, and linear regressions were used to quantify each ICMV– E_{v2} relationship. The 600 mm plate consistently produced stronger and less scattered correlations than the 300 mm plate, because its greater measurement depth better matches the influence depth of the roller. Mechanics-based indicators, in particular the vibration modulus E_{vib} , gave the highest correlations. The lighter roller yielded stronger correlations than the heavier one. The best combination, E_{vib1} measured by the lighter roller and correlated to E_{v2} from the 600 mm plate, reached a correlation coefficient of about 0.8. The correlations remain roller-dependent, confirming that machine-specific calibration is still required in current CCC practice.

5.2 Paper B

Nonlinear vibration response of a roller–soil system using finite element analysis with hypoplasticity

Wenjun Hua, Carl Wersäll, and Stefan Larsson
Manuscript to be submitted.

The paper presents a two-dimensional plane-strain FEM model of a vibratory roller compacting a granular layer, implemented in ABAQUS/Standard. The soil domain is bounded by infinite elements that absorb outgoing waves, and the roller is represented as an analytical rigid drum connected to a lumped frame mass through a vertical spring–dashpot isolation system. Four constitutive models with increasing complexity were compared: linear elastic, MC plasticity, modified DPC plasticity, and Hypo+IGS. The simulated surface deformation, depth-dependent stress–strain response, density evolution, and ICMVs were evaluated for different initial compaction states. The elastic model cannot capture the hysteretic nature of vibratory compaction. The MC model mainly showed shear-induced dilation. The DPC model represented compression plasticity, but its contractive zone remained limited. Among the models considered, Hypo+IGS gave the most physically consistent response for initially loose to dense gravel by capturing contractive volumetric response, void-ratio reduction, density-dependent stiffness, and distinct loading and unloading behavior. The results also showed that the depth of influence depends on the chosen response quantity: about 1.0–1.3 m based on settlement, 1.4–2.0 m based on strain, and 1.5–2.4 m based on density-related criteria. The vibration moduli, E_{vib1} and E_{vib2} , were more closely related to the simulated final density state than CMV or OMEGA. The normalized void-ratio reduction, $(e_0 - e)/(e_0 - e_d)$, showed the most consistent relationship with the roller response, with R^2 values of 0.92–0.97. The results identify Hypo+IGS as a suitable level of constitutive fidelity when the objective is to simulate cyclic densification, residual compaction potential, or ICMVs governed by the loading–unloading path.

5.3 Paper C

Compaction quality assessment based on machine learning with small datasets

Wenjun Hua, Carl Wersäll, and Stefan Larsson
Revised manuscript submitted to *the 6th International Conference on Geotechnics for Sustainable Infrastructure Development*, 2026.

The paper evaluates machine learning methods for estimating PLT moduli from roller measurements when only a small dataset is available. Sixty samples with matched roller measurements and PLT results from the full-scale trials were split into a training set of 48 samples and a test set of 12 samples. Two feature sets were prepared: Feature Set 1 contains five selected ICMVs (F_t , CEV, E_{vib1} , E_{vib2} , and OMEGA), while Feature Set 2 contains eight curated response characteristics extracted from acceleration signals and contact force–displacement curves. Six algorithms were compared:

MLR, RF, XGBoost, SVR, KNN, and the tabular foundation model TabPFN. All models were trained in a multi-output formulation that predicts E_{v1} and E_{v2} simultaneously, and SHAP values were computed to interpret the predictions. For Feature Set 1, SVR gave the best E_{v2} test result, with $R^2 = 0.34$ and $\text{RMSE} = 7.1$ MPa. For Feature Set 2, TabPFN gave the best E_{v2} result, with $R^2 = 0.45$ and $\text{RMSE} = 6.5$ MPa. The curated response characteristics outperformed the predefined ICMVs, indicating that the fixed ICMV formulas discard part of the information in the raw drum response. SHAP analysis identified the second-harmonic acceleration amplitude, loading and unloading stiffness, and displacement amplitude as key predictors of E_{v2} . The multi-output formulation also allowed the E_{v2}/E_{v1} ratio to be estimated directly, with the lowest $\text{RMSE} = 0.34$, obtained by SVR on Feature Set 2. The results show that curated vibration responses and data-driven modeling can complement ICMVs under limited data conditions, although the uncertainty in E_{v1} remains a practical limitation.

6 Conclusions and future work

6.1 Conclusions

This thesis investigated the reliability of CCC-based quality assurance for vibratory compaction of granular soil. The work combines full-scale tests, finite element analysis, and machine learning. For detailed conclusions from the individual studies, reference is made to the appended papers. The main conclusions are listed below.

- Linear relationships between ICMVs and the PLT-derived deformation modulus were established under controlled full-scale test conditions. The correlation strength depended on the selected indicator, roller, and plate diameter.
- The CA6500D produced higher PLT moduli and better uniformity in some cases, whereas the CA3500D gave stronger $ICMV-E_{v2}$ correlations and larger regression slopes. Additional passes increased E_{v1} and E_{v2} and reduced E_{v2}/E_{v1} , with diminishing gains and reduced uniformity at high pass numbers for the heavier roller.
- The 600 mm PLT plate was more suitable than the 300 mm plate for comparison with roller measurements. Its larger measurement volume better represents the depth interval affected by the vibratory roller and reduces the influence of local near-surface variability.
- Mechanics-based ICMVs, especially the vibration modulus E_{vib} , gave the strongest and most physically interpretable correlation with E_{v2} . The best combination in the test series, E_{vib1} from the CA3500D roller and the 600 mm PLT plate, gave a correlation coefficient of approximately 0.8.
- The sixteen evaluated ICMVs showed substantial redundancy and could be grouped into acceleration-based, loading-related, and unloading-related clusters. This indicates that a smaller set of representative indicators can describe much of the information contained in the full ICMV set.

- The numerical study showed that the soil constitutive model has a strong influence on the simulated roller–soil response. A linear elastic model cannot reproduce the hysteretic and irreversible response, and the MC model mainly produces shear-induced dilation rather than cumulative volumetric contraction. The DPC model predicted a limited contractive zone in the present simulations.
- Hypo+IGS gave the most consistent description of vibratory compaction because it couples stress level, void ratio, recent strain history, and small-strain stiffness. This makes it suitable for studying soil densification, stiffness evolution, residual compaction potential, and the physical origin of ICMVs.
- The numerical results showed that the compaction influence depth depends on the response quantity used to define it. Settlement indicated an influence depth of about 1.0–1.3 m, whereas density-related criteria gave larger depths of about 1.5–2.4 m.
- In the simulations, the vibration moduli $E_{\text{vib}1}$ and $E_{\text{vib}2}$ were more closely related to the final density state than CMV or OMEGA. The normalized void-ratio reduction, $(e_0 - e)/(e_0 - e_d)$, which represents the mobilized portion of the initially available compaction potential, showed the most consistent relationship with the roller response, with R^2 values of 0.92–0.97.
- The machine-learning study showed that nonlinear multi-output regression can estimate E_{v2} from roller measurements under the small-dataset conditions of the present study. For selected ICMVs, SVR gave the best E_{v2} result ($R^2 = 0.34$, RMSE = 7.1 MPa). For curated response characteristics, TabPFN gave the best E_{v2} result ($R^2 = 0.45$, RMSE = 6.5 MPa) without hyperparameter tuning.
- Selected response characteristics derived from the measured drum motion and contact force–displacement response gave better performance than predefined ICMVs. This indicates that the fixed ICMV formulas do not fully represent the information contained in the drum–soil interaction. SHAP analysis identified the second-harmonic acceleration amplitude, loading and unloading stiffness, and displacement amplitude as key predictors of E_{v2} .
- The simultaneous estimation of E_{v1} and E_{v2} made it possible to compute the E_{v2}/E_{v1} ratio continuously. This ratio is relevant for assessing the remaining compaction potential of a compacted layer, but its accuracy is limited by the weaker prediction of E_{v1} . In the present study, the lowest RMSE for this ratio was 0.34, obtained by SVR on the curated response characteristics.

In summary, the experiments identified which ICMVs are most closely related to the PLT modulus, the numerical study clarified how the simulated roller response and density-related state variables can be used to interpret ICMVs, and the machine-learning study showed how several response characteristics can be combined for continuous stiffness estimation. The results demonstrate the potential of CCC-based quality assurance, but they also show that machine-specific calibration and limited field data remain important practical constraints.

6.2 Future work

The following directions are proposed for the continuation of the work.

A stiffness-based ICMV with reduced machine dependence. The full-scale trials showed that the relationship between ICMVs and E_{v2} depends strongly on the roller. Further work should therefore focus on an indicator that more directly represents the absolute ground stiffness and is less sensitive to roller mass, excitation level, and operating mode. The aim is to reduce the need for machine-specific calibration in practical CCC.

Further validation of the FEM model. A numerical framework for evaluating simulated roller-integrated measurements has been established. The next step is to validate the simulated stress–strain response, density profile, and ICMVs against instrumented field or laboratory measurements before the model is used for broader parametric studies.

Investigation of compaction parameters and proof-rolling settings. The present full-scale trials were carried out at fixed vibration frequency, amplitude, and travel speed. Future trials should vary these parameters systematically and evaluate their influence on both ICMVs and ICMV– E_{v2} correlations. Of particular interest is whether a proof-rolling pass can improve the correlations without disturbing an already compacted layer.

Synthetic datasets for remaining compaction potential. The high-fidelity FEM model can be used to generate synthetic datasets covering different soil states, roller properties, and operating parameters. These datasets can provide training and testing data for machine-learning models that estimate both the achieved compaction effect and the remaining compaction potential. This physics-informed approach is intended to reduce the limitations caused by the small number of paired CCC–PLT measurements available from full-scale testing.

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Paper A

Correlating continuous compaction measurement to plate load tests for quality assurance

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Abstract: Continuous compaction control (CCC) offers a promising alternative to conventional spot tests for earthwork quality assurance. However, establishing reliable correlations between intelligent compaction measurement values (ICMV_s) and traditional stiffness metrics, such as the deformation modulus (E_{v2}) from static plate load tests (PLT), remains a challenge. This study investigated the influence of PLT plate size and vibratory roller type on these correlations through a series of full-scale compaction tests conducted on a granular soil bed. Two plate diameters (300 and 600 mm) and two rollers with different static linear loads (36 and 65 kg/cm) were employed. Sixteen ICMV_s spanning acceleration-, mechanics-, and energy-based categories were computed and correlated with E_{v2} . The results showed that the 600-mm plate, despite producing lower E_{v2} values, consistently yielded stronger correlations with the representative ICMV_s. The lighter roller produced stronger correlations than the heavier roller, likely due to reduced contact loss and better alignment of measurement depths. Mechanics-based ICMV_s performed best, with the vibration modulus (E_{vib}) during the loading phase showing the strongest correlation (R up to 0.8). These findings confirm that E_{vib} is a suitable indicator for compaction quality control, suggest that the larger plate is preferable for calibration purposes, and underscore the need for machine-specific calibration.

Keywords: Vibratory compaction, Plate load test, Intelligent compaction measurement values, Deformation modulus, Continuous compaction control

1 Introduction

Reliable quality control and quality assurance (QC/QA) of compaction are crucial for ensuring the bearing capacity and durability of earthworks while minimizing maintenance costs over the service life. However, conventional spot tests for compaction QA, such as the repetitive static plate load test (PLT), are labor-intensive and time-consuming. Furthermore, they offer only limited spatial coverage and provide delayed, retrospective feedback, as they are typically performed post-compaction. In contrast, continuous compaction control (CCC) [1,2], also known as intelligent compaction (IC), utilizes accelerometers mounted on rollers to deliver intelligent compaction measurement values (ICMV_s) over large areas in real time, where higher ICMV values generally indicate better compaction quality. This technology enables real-time operational adjustments to reduce the risk of over- or under-compaction.

Based on their underlying principles and calculation methods, ICMV_s can be classified into three main categories: acceleration-based, such as compaction meter value (CMV) [2] and continuous compaction value (CCV) [3]; mechanics-based, such as roller-integrated stiffness

(k_s) [4] and vibration modulus (E_{vib}) [5]; and energy-based, such as OMEGA [6] and machine drive power (MDP) [7]. Although various ICMVs have been proposed in the literature, a comprehensive comparative analysis is still lacking. Furthermore, their applicability to different compacted materials and their sensitivity to various compaction parameters can differ significantly. For instance, ICMVs are influenced not only by soil conditions [8], including soil type, moisture content, and gradation, but also by factors related to the compaction process itself [9], such as roller weight, vibration amplitude, frequency, and travel speed. Therefore, examining the interrelationships among different ICMVs and their dependence on rollers is essential for guiding the selection of suitable QA indicators.

Beyond identifying weak areas, advanced CCC-based QA involves establishing correlations between ICMVs and spot-test results within a calibration area to determine a target ICMV, often through methods like linear regression. The calibrated relationships are specific to the material and site conditions. Such relationships have been investigated in numerous studies. For instance, Floss et al. [10] found that correlation coefficients between CMV and PLT moduli were higher than those between CMV and density. However, field test results also showed that CMV exhibited substantial local variability [11,12] and might be insufficient for evaluating ground stiffness in areas affected by changes in roller operating conditions [13]. By averaging the data for each roller pass, Thompson et al. [7] found a strong correlation between MDP and in-situ measurements, such as dry unit weight. However, poor or no correlation was observed using collocated measurements. Similarly, Meehan et al. [14] concluded that point-by-point linear regression analyses between CMV, MDP and various in-situ test results yielded poor correlations. Poor correlation between E_{vib} and various stiffness measurements, such as Geogauge, falling weight deflectometer (FWD), and dynamic cone penetrometer (DCP), was also reported by Peterson [15] and Rahman et al. [16]. Both studies attributed this discrepancy to the depth- and stress-dependence of soil modulus and to differences in the influence depth across measurement techniques. Barman et al. [17] demonstrated that the Intelligent Compaction Analyzer (ICA) modulus for stabilized subgrades correlated well with the subgrade modulus back-calculated from FWD, DCP, and laboratory resilient modulus. However, the limited number of data points and the inclusion of only one compaction level in this study restricted the generalizability of these findings. It is reported that a good correlation between CMV and FWD deflection can be obtained only when the moisture content is consistent [18].

In recent years, advanced evaluation methods such as machine learning (ML) have gained prominence in compaction quality assessment. Using laboratory test results with over 1000 records, artificial neural networks have effectively predicted the maximum dry density (MDD) and optimum moisture content (OMC) for cohesionless [19] and cohesive soils [20]. In field applications, an ML model has been proposed to infer soil density from the LWD modulus [21]. Additionally, ML models using multi-domain vibration features [22] and multi-scenario compaction data [23] have been developed to estimate the degree of compaction obtained from sand cone tests. Data augmentation has been employed to address the scarcity of field data [24]. However, most existing ML models remain empirical and lack sufficient interpretability. They also require careful calibration for broader field transferability and entail complex implementation.

The literature suggests that no universally reliable correlation has yet been established, and consistent results that would allow the direct application of CCC to compaction QA remain elusive. Additionally, field studies are often complicated by variable conditions, making it difficult to properly evaluate the performance of different ICMVs. To address this gap, a series of full-scale compaction tests was conducted in a laboratory environment, where the

aforementioned confounding factors were controlled as far as possible. The performance of various ICMVs calculated from the same accelerometer data was evaluated in terms of their correlation with the deformation modulus E_{v2} measured by PLT. In addition, two supplementary objectives were considered: (a) to compare deformation moduli measured using different plate sizes, and (b) to compare ICMVs measured with different rollers at varying numbers of passes. It should be noted that the main objective of this study was to evaluate the correlation between ICMVs and E_{v2} under consistent test conditions, rather than to optimize compaction performance.

To the best of the authors' knowledge, this paper presents the first comprehensive assessment of a broad set of ICMVs under consistent test conditions. The study quantifies the range, variability, and interrelationships among these ICMVs and identifies redundant and complementary information. A key contribution is the systematic evaluation of how two practical factors, specifically PLT plate diameter and roller type, influence the ICMV– E_{v2} correlation. Taken together, these analyses clarify which ICMVs or categories thereof are best suited for QA, provide practical recommendations for selecting plates and rollers, and highlight the importance of machine-specific calibration.

2 Methodology

2.1 Test scheme

Five full-scale trials were designed and conducted at the compaction lab of Dynapac Compaction Equipment AB in Karlskrona, Sweden. The test bed was a 27 m by 7 m bottomless tank bounded by vertical concrete walls, as shown in **Fig. 1**. The test surface was positioned in the center of the test bed and divided into two adjacent lanes, each 22 m long and 2.13 m wide, matching the drum width. The distance from the lane centerline to the surrounding wall was 2.44 m, which is greater than the drum width. The layouts of measurement locations are shown in **Fig. 2**. For Trials 3, 4, and 5, the test surface was further subdivided into three areas, each separated by a 2 m buffer. Although the absolute deformation moduli (E_v) and ICMV values may differ from those in open-field conditions, comparisons of plate diameters (D), roller types, and ICMVs remain valid under the same boundary conditions.

At the beginning of each trial, the soil was loosened to an approximate depth of 0.7 m with an excavator, and the test surface was then manually graded further. After a preparatory static pass at 1 m/s, the PLT measurement locations were marked on the surface with spray paint. Subsequently, the test area was subjected to a specified number of vibratory passes (N), followed by two static passes at the same speed of 1 m/s to mitigate the adverse effects of surface loosening. The compaction was carried out by alternating between two test lanes every two consecutive passes. Within each lane, the designated roller traveled back and forth in alternating directions, so that odd- and even-numbered passes represent forward and backward rolling, respectively, with each trip counting as one pass. This ensured that the number of forward and backward passes was the same, thereby balancing and averaging out the influence of travel direction over the compaction sequence.

Finally, after conditioning overnight for about 24 hours, PLTs [25] were conducted at the marked locations along the lane centerline. This conditioning period allowed for minor particle rearrangement and better uniformity before further testing. The same conditioning period and

preparation protocol were consistently applied across all trials. This facilitates more uniform initial soil conditions throughout the test area, thereby improving the reliability of the results and enabling effective comparisons between plate sizes, rollers, and ICMVs.

The test matrix is summarized in **Table 1**. Across the five trials, a total of 116 PLTs were conducted. In Trials 1 and 2, PLTs were conducted after the sixth pass, with measurement points spaced 2 m apart along the rolling direction. Six passes were selected based on industry practice and previous studies [26,27] to ensure satisfactory compaction quality while avoiding over-compaction. PLTs with two plate diameters ($D = 300$ and 600 mm) were alternated to maximize the spacing between adjacent test points, resulting in 11 measurements for each D .

In Trials 4 and 5, N varied across three areas ($N = 8, 4$, and 2 for Areas 1, 2, and 3, respectively). This configuration yielded eight PLT measurements for each selected N . This approach was designed to capture a wide range of compaction states for subsequent analyses and to enable direct comparison with the results from Trials 1 and 2 at $N = 6$. The lower bound was set to two passes because it produced more stable results than a single pass, as indicated by the relationship between ICMVs and N in Section 3.2.2. Conducting a PLT after one pass also risks premature test termination due to excessive settlement, which could compromise data validity.

To evaluate the effect of the additional static compaction following vibratory compaction, N was set to 6 for Areas 2 and 3 in Trial 3, with Area 2 excluding the final static passes. Note that in Trials 3, 4 and 5, only the plate with $D = 600$ mm was used, and the measurement spacing was reduced to 1.3 m. This closer spacing was necessary to obtain a sufficient number of data points for statistically meaningful regression analysis while maintaining a reasonable distance between test locations.



Fig. 1. Test bed and roller in operation.

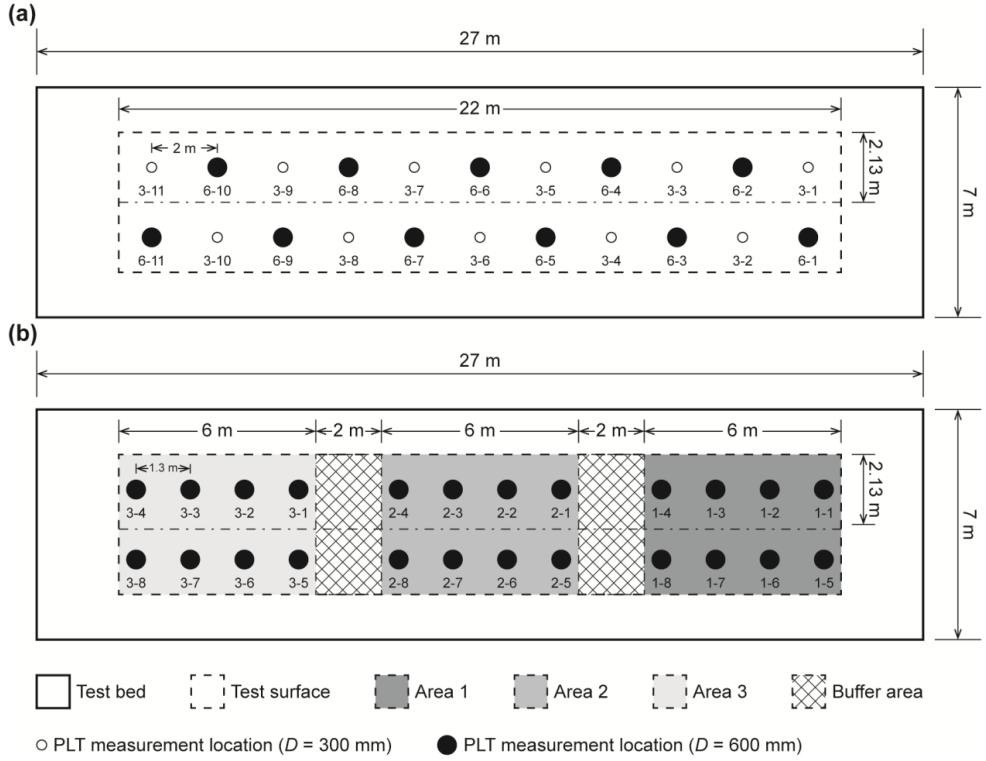


Fig. 2. Test layouts for different trials: (a) Trials 1 and 2, and (b) Trials 3, 4 and 5.

Table 1. Test matrix.

Trial No.	D (mm)	Roller	N^a
1	300 & 600	CA6500D	6
2	300 & 600	CA3500D	6
3	600	CA6500D	8, 6 ^b , 6
4	600	CA3500D	8, 4, 2
5	600	CA6500D	8, 4, 2

^a Comma-separated N values denote the number of vibratory passes applied to each test area.

^b PLTs were performed after six vibratory passes, without additional static compaction.

2.2 Materials

The test material was well-graded gravel (GW), a common embankment fill material in Sweden, with almost no oversized particles. It consisted of crushed rock with a coefficient of uniformity $C_u = 107$, coefficient of curvature $C_c = 1.5$, specific gravity $G_s = 2.7$, and a maximum density of 2230 kg/m^3 determined by the modified Proctor test. The particle size distribution was determined in accordance with the specification [28], and the sieve test results are shown in **Fig. 3**. The gradation fell within the grading envelope for base course materials in the compacted layers of a paved road [29], with a maximum particle size of 32 mm.

The moisture content (w) was controlled at approximately 3%, corresponding to the natural moisture content (NMC). The OMC was around 6%, as determined by both the standard and modified Proctor tests [30]. Previous studies have shown that the much greater compaction effort applied by a roller can result in an OMC lower than that obtained from the Proctor test. The test bed was covered with tarpaulins between operations to prevent water evaporation. The surface w was measured by collecting six evenly distributed samples along both lanes at the start and end of each trial. The results showed that the average w across trials was 3.3% at the beginning and 2.8% at the end, with both coefficients of variation (CV) being 2%. This indicates that w was effectively maintained throughout testing.

Soil stiffness is sensitive to w variations, especially near the OMC. For example, similar dry density may be achieved at two w on opposite sides of the OMC, while the corresponding moduli differ substantially [18,31]. However, this effect is generally less pronounced in unbound granular materials such as the tested gravel than in cohesive soils. Testing at the NMC in an indoor laboratory with stable temperature and humidity therefore helped reduce moisture-induced variability in stiffness and ensure consistent conditions across trials. Other moisture conditions and soil types were not investigated in this study.

The layer to be compacted was 1 m thick and was underlain by rockfill. Since compaction tests have been conducted at the same location for over forty years, the underlying fill can be considered well compacted. Therefore, the underlying support condition was assumed to be consistent across trials and had little influence on the comparative conclusions.

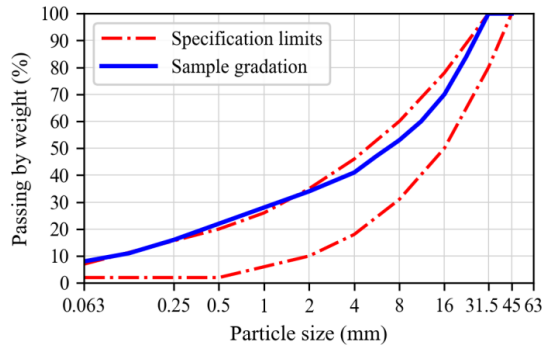


Fig. 3. Particle size distribution curves of the test material.

2.3 Equipment

The compaction equipment comprised two Dynapac single-drum vibratory rollers: a CA3500D and a CA6500D. These models are named according to their approximate static linear loads, with detailed operating parameters listed in **Table 2**. The CA6500D was selected to represent a heavy-duty roller with high compaction capability. The CA3500D, a lighter and more common model, was chosen to provide a clear contrast with approximately half the static linear load.

During vibratory compaction, both rollers were operated exclusively at their high-amplitude settings and a fixed vibration frequency (f) of 24 Hz. This frequency was chosen as a precaution against “double-jumping”, a phenomenon where the drum intermittently loses contact with the ground and re-impacts only every second excitation cycle as the compacted material stiffens.

This can introduce noise and instability into the ICMV measurements, as also demonstrated by field tests [13]. Therefore, selecting a lower f than the maximum values listed in **Table 2** helps ensure more stable data collection, especially during later passes when the ground is stiffer.

In practice, f is adjustable, and a higher value does not necessarily result in better compaction. For example, the automatic frequency control (AFC) system of the CA6500D, which is the standard setting, operates over a range of 17–28 Hz [32]. Field tests on sub-ballast rock-fill have reported an average f of about 19 Hz under AFC, which produced significantly higher stiffness than at a fixed f of 28 Hz [33]. Similar findings have also been reported in the literature [8].

Table 2. Operating parameters of vibratory rollers at high-amplitude and maximum frequency settings.

Property	CA3500D	CA6500D
Drum mass (kg)	4040	5300
Frame mass (kg)	3565	8470
Operating mass (kg)	13800	21000
Drum width (m)	2.13	2.13
Drum diameter (m)	1.518	1.546
Static linear load (kg/cm)	36	65
Nominal amplitude (mm)	1.9	2.1
Vibration frequency (Hz)	31	29
Centrifugal force (kN)	280	360
Eccentric moment (kg·m)	7.31	10.31

The measurement equipment primarily consisted of a biaxial accelerometer mounted on the roller drum, a data acquisition system, and an onboard computer. During the compaction, the drum's vertical and horizontal accelerations were recorded. Additionally, each time the drum passed over a marked spot, a handheld trigger connected to the data acquisition system was manually pressed to generate a pulse signal, which was used to precisely locate those spots. The eccentric position sensor integrated within the drum, which measures the angular position of the rotating shaft, was used to determine the phase lag. The onboard computer recorded all signals at a 2 kHz sampling rate, which were then transferred to a personal computer for data analysis.

During a PLT, normal stress is applied to a circular loading plate in increments over two loading cycles, and the corresponding settlement is measured using a displacement transducer. The deformation modulus from the second cycle (E_{v2}) is used to represent ground stiffness, and the ratio of the moduli from the first and second cycles (E_{v2}/E_{v1}) is considered a measure of residual compaction potential.

A knowledge gap remains regarding how plate size affects the correlation between PLT results and ICMVs. To address this, two plate sizes were used: a standard 300-mm diameter plate and a 600-mm diameter plate. The roller used in each trial also served as the counterweight for the PLT loading. Maximum applied stresses for the first loading cycle were 500 kPa (300-mm plate) and 250 kPa (600-mm plate). For the reloading, these values were 450 kPa and 200 kPa, respectively. Other plate sizes (e.g., 762 mm [25,34]) were not used because the larger spacing required between test locations was impractical given site constraints and the need for statistically sufficient data points for each plate size.

2.4 Calculation of ICMVs

Raw accelerometer data were recorded at a sampling frequency of 2 kHz during compaction, from which sixteen ICMVs across three categories were calculated. This section briefly introduces the ICMVs analyzed in this study. They are summarized in **Table 3**. Detailed calculation methods are illustrated in Appendices A, B, and C.

These ICMVs can be categorized into three groups: acceleration-based, mechanics-based, and energy-based. Acceleration-based ICMVs are derived from the time-domain and frequency-domain characteristics of the vertical acceleration signal. Typical time-domain metrics include peak value (a_p), root-mean-square value (a_{rms}), and crest factor (CF) [35,36]. Two recent indicators, the maximum velocity compaction value (MVCV) [37] and the kinetic energy compaction value (KECV) [38], have been proposed and represent the peak downward velocity and the corresponding maximum kinetic energy of the vibrating drum within a vibration cycle. Frequency-domain ICMVs are defined as amplitude ratios of different harmonic components of the signal. Among these, the compaction meter value (CMV) [2] was first proposed and remains the most widely used. Variants such as acceleration intelligent compaction value (AICV) [39], compaction control value (CCV) [3], total harmonic distortion (THD) [40], and turbulence factor (F_t) [41] also consider the influence of higher-order harmonic and subharmonic components.

In contrast to empirical acceleration-based indices, mechanics-based ICMVs are derived from the hysteresis curve of contact force–drum displacement. Representative indices include the roller-integrated stiffness (k_s) [4], vibration modulus (E_{vib}) [5], and vibration compaction value (VCV) [42]. These indices can be further refined by analyzing the hysteresis curve to distinguish between the loading and unloading phases within a single vibration cycle. Specifically, the stiffness and modulus during the loading phase are represented by k_1 and E_{vib1} , while those during the unloading phase are described by k_2 and E_{vib2} . The overall values for the entire cycle are denoted as k_b and E_{vib} . These ICMVs are physically meaningful and more closely related to the mechanical properties of compacted materials, such as E_{v1} and E_{v2} [43,44].

Recognizing that compaction is an energy transfer process from the roller to the ground, several energy-based values have been proposed. These include OMEGA [6], defined as the area of the force–displacement hysteresis curve, and machine drive power (MDP) [7], which represents the propel energy required to overcome rolling resistance. More recently developed ICMVs, such as those derived from advanced signal analysis, including the dissipation measured value (DMV) [45,46] and compaction energy value (CEV) [47–49], have also been introduced. However, their effectiveness requires further verification. This study also included the compaction power per unit volume (E) [50], which represents the total compaction work exerted on a unit volume of material after a certain N .

Table 3. ICMVs analyzed in this study.

Category	Indicator	Formula	Ref.
Acceleration	CMV	$CMV = C \times \frac{A_{2\omega}}{A_{\omega}}$	(1) [2]
	AICV	$AICV = C \times \frac{A_{1.5\omega} + A_{2\omega} + A_{2.5\omega}}{A_{0.5\omega} + A_{\omega}}$	(2) [39]
	CCV	$CCV = C \times \frac{A_{0.5\omega} + A_{1.5\omega} + A_{2\omega} + A_{2.5\omega} + A_{3\omega}}{A_{0.5\omega} + A_{\omega}}$	(3) [3]
	THD	$THD = C \times \frac{\sqrt{A_{2\omega}^2 + A_{3\omega}^2 + \dots + A_{6\omega}^2}}{A_{\omega}}$	(4) [40]
	F_t	$F_t = \frac{F_s}{(m_d + m_f)g} \cdot \frac{A_{1.5\omega} + A_{2\omega} + A_{2.5\omega} + A_{3\omega} + A_{3.5\omega} + A_{4\omega}}{A_{0.5\omega} + A_{\omega}}$	(5) [41]
	CF	$CF = \frac{a_p}{a_{rms}} = \frac{\max\{ a_i \}}{\sqrt{\frac{1}{n} \sum_{i=1}^n a_i^2}}$	(6) [35,36]
Mechanics	k_s	$k_s = \Omega^2 \left(m_d + \frac{m_0 e_0 \cos \varphi}{z_d} \right)$	(7) [4]
	E_{vib}	$z_d = \frac{1-v^2}{E_{vib}} \cdot \frac{F_s}{L} \cdot \frac{1}{\pi} \cdot \left(1 + 2 \ln \frac{4L}{b} \right)$	(8-a) [5]
		$b = \sqrt{\frac{16}{\pi} \cdot \frac{R(1-v^2)}{E_{vib}} \cdot \frac{F_s}{L}}$	(8-b)
Energy	DMV	$DMV = \pi \omega_0^3 \sum_{i=1}^n \frac{A_i^2}{\omega_i^3}$	(9) [45,46]
	CEV	$H(\omega, t) = \text{Real} \sum_{i=1}^n a_i(t) e^{j \int \omega_i(t) dt}$	(10-a)
		$h(\omega) = \int_0^T H(\omega, t) dt$	(10-b) [47–49]
		$CEV = \sum_{i=1}^n h(\omega_i)$	(10-c)
	OMEGA	$OMEGA = \oint_{2T} (m_d \ddot{z}_d + (m_d + m_f)g - m_0 e_0 \Omega^2) \dot{z}_d dt$ (11)	[6]
	E	$E = 2A \left(W + \frac{\pi F_s}{4} \cdot \frac{fN}{LhV} \right)$	(12) [50]

3 Results and discussion

3.1 Analysis of PLT results

Higher E_{v2} values reflect greater soil stiffness, which in turn indicates more effective compaction effort. The E_{v2}/E_{v1} ratio is often regarded as an indicator of the residual compaction potential in the subgrade. Specifically, a lower ratio suggests that limited compaction potential remains, i.e., that a significant portion of the achievable compaction has already occurred. Notably, E_{v1} represents not only the stiffness of the subgrade but also the initialization of contact between the loading plate and the soil. Consequently, the ratio is affected by the initial conditions prior to full contact and can therefore be misleading. This is particularly relevant for well-compacted soils, where factors other than stiffness may influence E_{v1} . The ratio is presented here for completeness but should be interpreted with caution.

3.1.1 Comparisons across plates and rollers

Table 4 summarizes the PLT results for the 300-mm and 600-mm plates after compaction with the CA3500D and CA6500D rollers. Mean E_{v1} values differed by less than 2% between the two D . A Wilcoxon Rank-sum test [51] confirmed that both E_{v1} and E_{v2}/E_{v1} were independent of D . This consistency in E_{v1} indicates uniform initial soil conditions. However, a statistically significant difference was observed for the E_{v2} ($p < 0.05$). The larger plate yielded a 5–7% lower mean E_{v2} than that of the smaller plate.

Regarding variability, the 600-mm plate showed a larger CV for E_{v1} , likely due to increased initial contact imperfections over a larger area. Conversely, it produced a slightly lower CV for E_{v2} . The observed reduction in both the mean and variability of E_{v2} for the larger plate can be attributed to two primary factors. First, the lower stresses applied to it may induce less soil hardening. Second, its greater measurement depth, per the Boussinesq solution, averaged stiffness over deeper soil layers that were less stiff.

A comparison between the two rollers shows that the mean E_{v1} values were very similar (relative difference less than 2%), confirming consistent initial soil conditions across the trials. The CA6500D produced significantly larger E_{v2} values and E_{v2}/E_{v1} ratios than the CA3500D ($p < 0.05$), with a mean E_{v2} value 7–10% higher. This can be attributed to its greater static weight and ground contact force during compaction. As indicated by the consistently lower CV, the CA6500D achieved better compaction uniformity due to its larger and deeper influence zone, resulting in greater soil homogenization. These findings highlight the importance of selecting an appropriate roller to achieve the desired soil stiffness and uniformity.

Table 4. Summary of PLT metrics for 300-mm and 600-mm diameter plates.

Metric	D (mm)	E_{v1} (MPa)		E_{v2} (MPa)		E_{v2}/E_{v1} (–)	
		CA3500D	CA6500D	CA3500D	CA6500D	CA3500D	CA6500D
Mean	300	39.3	38.8	109.6	117.7	2.8	3.0
	600	38.7	38.5	102.1	111.9	2.7	2.9
CV	300	8%	6%	6%	6%	7%	4%
	600	13%	8%	5%	4%	9%	7%

3.1.2 Variation of E_v values with N

Fig. 4 illustrates the evolution of PLT metrics from the 600-mm plate as a function of the number of passes. The bars represent mean values and the error bars denote standard deviation (SD). The transparent bars at $N = 6$ are included for reference from Trials 1 and 2.

For both rollers, further compaction increased stiffness (E_{v1} and E_{v2}) and decreased the remaining compaction potential (E_{v2}/E_{v1}). A direct comparison highlights the CA6500D's superior compaction capability. It achieved significantly higher E_{v2} at $N = 4$ and $N = 6$ than the CA3500D ($p < 0.01$), with mean values approximately 10% higher. The CA6500D reached nearly identical values at $N = 2$ and $N = 4$ as the CA3500D did at $N = 4$ and $N = 8$, respectively. The mean E_{v1} and E_{v2} values for both rollers increased only slightly from $N = 4$ to $N = 6$ (less than 1.4 and 2 MPa, respectively). This supports the selection of six passes as a stable condition for comparing plate diameters.

The CA6500D generally provided better uniformity up to $N = 6$, as evidenced by its smaller SD in E_{v1} and E_{v2} . For example, the SD of E_{v2} at $N = 4$ was 3.6 MPa and was 56% smaller than that for the CA3500D. However, its variability spiked dramatically at $N = 8$, with an SD of 9.3 MPa in E_{v2} that was 44% larger than that for the CA3500D. This trend, combined with a negligible increase (only 1.6%) in mean E_{v2} from $N = 4$ to $N = 8$, suggests the onset of inefficiency. Excessive compaction energy may begin to disturb the aggregate structure, leading to reduced uniformity. This phenomenon also explains why the mean E_{v1} for the CA6500D was lower than that for the CA3500D at $N = 8$. The structural disturbance resulted in a loosened and less uniform surface condition than that produced by the CA3500D. Further details on the surface loosening effect are provided in Appendix D.

At $N = 2$, the CA3500D displayed a higher E_{v2}/E_{v1} , indicating greater remaining compaction potential. However, by $N = 4$, this trend reversed. Despite the CA6500D producing a higher E_{v2}/E_{v1} from $N = 4$ to $N = 8$, the increase in E_{v2} was less than 2%. Conversely, the CA3500D showed greater stiffness improvement, with E_{v2} increasing by 11%. This suggests that E_{v2}/E_{v1} is a relative ratio and should only serve as a supplementary indicator for assessing compaction quality.

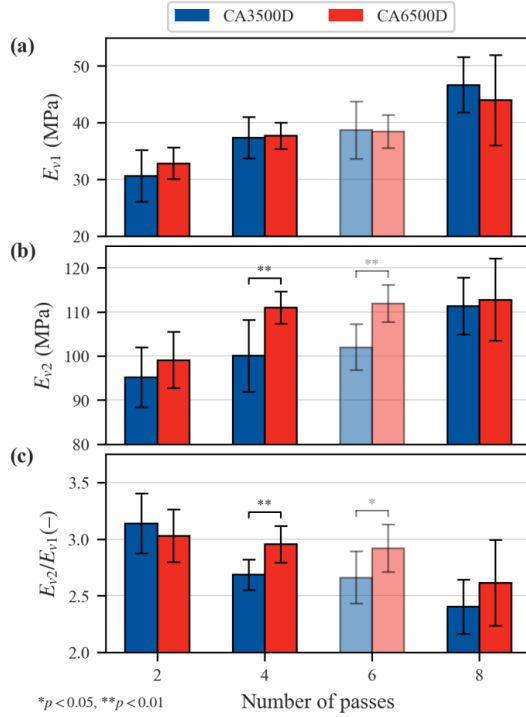


Fig. 4. Variation of PLT results measured by the 600-mm plate with N : (a) E_{v1} , (b) E_{v2} , and (c) E_{v2}/E_{v1} .

3.2 Analysis of ICMVs

3.2.1 Interrelationships among ICMVs

Although many ICMVs have been proposed, a comprehensive statistical analysis of their range, variability, and relationships remains lacking. This section addresses this gap and proposes a compact grouping of ICMVs. The results clarify which ICMVs provide unique versus overlapping information and help select key indicators for calibration with QA test results.

Table 5 summarizes the descriptive statistics of ICMVs, which are calculated from data across all trials and passes. Along with the minimum and maximum values, two dimensionless ratios are included to characterize the dynamic range and variability of each ICMV. Both the percentile ratio P95/P5 and the interquartile range to median ratio (IQR/median) are less sensitive to outliers. For example, the P95/P5 ratio of F_t is a more realistic measure of its response range, as the near-zero minimum would otherwise skew the result. Note that the ICMVs are sorted by their P95/P5 ratios.

CF showed the narrowest range and the lowest variability, indicating limited discriminative resolution. CEV and DMV maintained a narrow range, while OMEGA, k_2 , and E_{vib2} had a moderate range and remained stable. Harmonics-based ICMVs (CMV, AICV, THD, CCV) and other stiffness-based ICMVs (k_b , k_1 , E_{vib} , E_{vib1}) displayed wider ranges with greater variability.

F_t and E exhibited broad ranges and substantial variability, and the significant variability of E arises from multiple operational parameters.

This analysis indicates that an effective ICMV should strike a balance between a wide dynamic range and controlled variability, thereby ensuring sensitivity to compaction states and reliable measurements.

Table 5. Descriptive statistics of ICMVs across trials 1–5 and passes 1–8.

Indicator	Unit	Min	Max	P95/P5	IQR/median
CF	–	1.5	2.0	1.3	0.10
CEV	$\times 10^3 \text{ m}^2/\text{s}^3$	2.5	6.0	2.2	0.32
DMV	$\times 10^3 \text{ m}^2/\text{s}^4$	6.9	30.7	2.2	0.33
Omega	kJ	0.3	1.3	3.1	0.49
k_2	MN/m	68.1	272.8	3.2	0.35
E_{vib2}	MPa	122.0	534.0	3.4	0.38
CMV	–	10.9	72.7	4.1	0.54
k_b	MN/m	24.3	133.2	4.1	0.57
AICV	–	14.4	96.7	4.4	0.57
k_1	MN/m	11.2	86.4	4.4	0.54
THD	–	4.8	33.7	4.4	0.58
E_{vib}	MPa	39.8	246.4	4.5	0.61
E_{vib1}	MPa	17.0	154.0	4.9	0.58
CCV	–	4.8	42.1	4.9	0.68
F_t	–	0.0	1.5	9.8	0.97
E	kJ/m ³	16.8	371.5	17.0	1.36

The interrelationships among different ICMVs are visualized in **Fig. 5**. This integrates three complementary analyses: hierarchical clustering, principal component analysis (PCA), and a quantitative assessment of intra-cluster redundancy and inter-cluster similarity.

First, **Fig. 5(a)** presents a hierarchically clustered heatmap based on Spearman correlation coefficients (r). This non-parametric approach was chosen for its robustness to non-normality and outliers, and its ability to capture nonlinear monotonic relationships. The heatmap shows that most ICMVs are strongly and positively intercorrelated ($r > 0.8$, $p < 0.01$), except for CF and DMV, which form singleton branches in the clustering and are therefore considered outliers. Hierarchical clustering, using the Euclidean distance of $(1 - r)$ as the dissimilarity metric, partitions the remaining ICMVs into three distinct clusters:

- Cluster 1 (blue): E, F_t , CMV, THD, CCV, AICV.
- Cluster 2 (orange): CEV, k_b , E_{vib} , k_1 , E_{vib1} .
- Cluster 3 (green): OMEGA, k_2 , E_{vib2} .

This clustering is consistent with the physical derivation of the indicators, where acceleration-based ICMVs group together in Cluster 1. While supporting the general classification, it also reveals a subtle aspect: stiffness-based ICMVs are split into two clusters, with Cluster 2

associated with the loading phase of the drum–soil interaction and Cluster 3 with the unloading phase. Furthermore, energy-based ICMVs do not form a single separate cluster.

PCA was then applied to validate and interpret this grouping. The score plot in **Fig. 5(b)** projects the ICMVs onto a two-dimensional space defined by the first two principal components (PC1 and PC2), which collectively explain 73% of the total variance (i.e., the overall variability across all ICMVs). ICMVs from different clusters are distinctly located in separate quadrants. PC1 distinguishes acceleration-related information from stiffness- and energy-related information. PC2 differentiates loading and unloading differences. Harmonics-based ICMVs are highly redundant, whereas energy-based ICMVs, especially OMEGA, provide relatively independent additional information. CEV is related to loading stiffness, while E is more closely associated with acceleration. Larger pairwise distances in this plot align with the weaker correlations in **Fig. 5(a)**, such as between OMEGA and harmonics-based ICMVs.

Finally, **Fig. 5(c)** compares the average intra- and inter-cluster correlation coefficients ($\bar{r}_{\text{intra}}$ and $\bar{r}_{\text{inter}}$). The dark bars and the white numerical labels on the left side represent $\bar{r}_{\text{inter}}$, while the light bars and the black numerical labels on the right represent $\bar{r}_{\text{intra}}$. Note that, for each ICMV, $\bar{r}_{\text{intra}}$ exceeds $\bar{r}_{\text{inter}}$, indicating strong redundancy within clusters ($\bar{r}_{\text{intra}} = 0.92\text{--}0.98$) and high similarity between clusters ($\bar{r}_{\text{inter}} = 0.80\text{--}0.88$). THD, k_1 , and k_2 have the highest $\bar{r}_{\text{intra}}$ within their respective clusters, indicating that they are highly representative. Conversely, E, CEV, and OMEGA exhibit the lowest $\bar{r}_{\text{intra}}$, and the largest differences between $\bar{r}_{\text{intra}}$ and $\bar{r}_{\text{inter}}$ are observed in THD, CEV, and OMEGA, highlighting their specificity. While E has the highest $\bar{r}_{\text{inter}}$, it acts as a “glue” variable, which matches its position in **Fig. 5(b)**. This is likely attributable to its formulation, which explicitly combines multiple operational parameters.

These results support a dimensionality-reduction strategy for multivariate regression or machine-learning applications. To balance representativeness and distinctiveness, key ICMVs can be selected from each cluster, prioritizing those with high $\bar{r}_{\text{intra}}$ and low $\bar{r}_{\text{inter}}$.

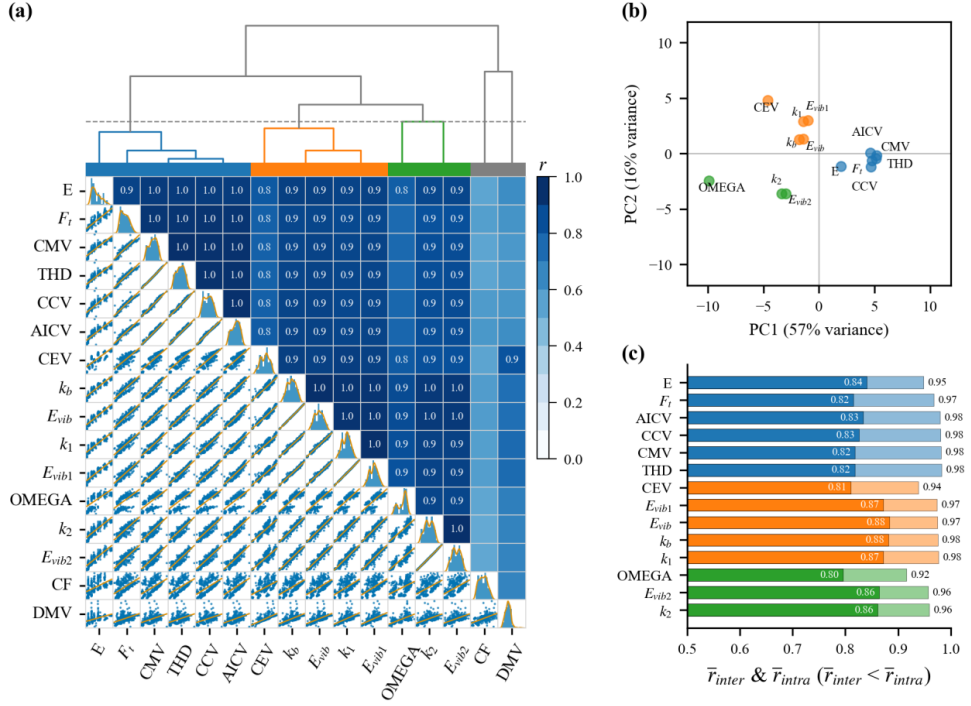


Fig. 5. Interrelationships among ICMVs: (a) hierarchically clustered heatmap, (b) PCA score plot, and (c) bar chart of average correlation coefficients.

3.2.2 Variation of ICMV values with N

Based on the clustering results in Section 3.2.1, CMV, E_{vib1} , and E_{vib2} were selected as representative indicators of the three clusters given their high $\bar{r}_{intra}$ values and common use in practice. E, CEV, and OMEGA were also selected because they are all energy-based indicators but exhibit distinct patterns across clusters, as reflected by their relatively low $\bar{r}_{inter}$ values. **Fig. 6** illustrates the variation of these ICMVs with N for both rollers. The mean values at each PLT measurement point are used, and the error band represents $\pm$ SD. All ICMVs displayed a general upward trend, while the variability of E_{vib2} during later passes became notably high. The CA6500D consistently produced higher ICMV readings than the CA3500D, especially in OMEGA, where values are approximately double.

Linear regression equations are presented to offer insights into the compaction progress without displaying fitting curves. CMV and E show a high coefficient of determination (R^2). The near-perfect linearity of E is inherent to its definition in **Eq. (12)**. In contrast, E_{vib1} and CEV exhibit a zigzag pattern, in which the values for odd-numbered passes are consistently lower than those for the subsequent even-numbered passes. This indicates that these indicators are sensitive to the change in drum rolling direction. The low R^2 for OMEGA indicates that compaction energy evolves nonlinearly with increasing N .

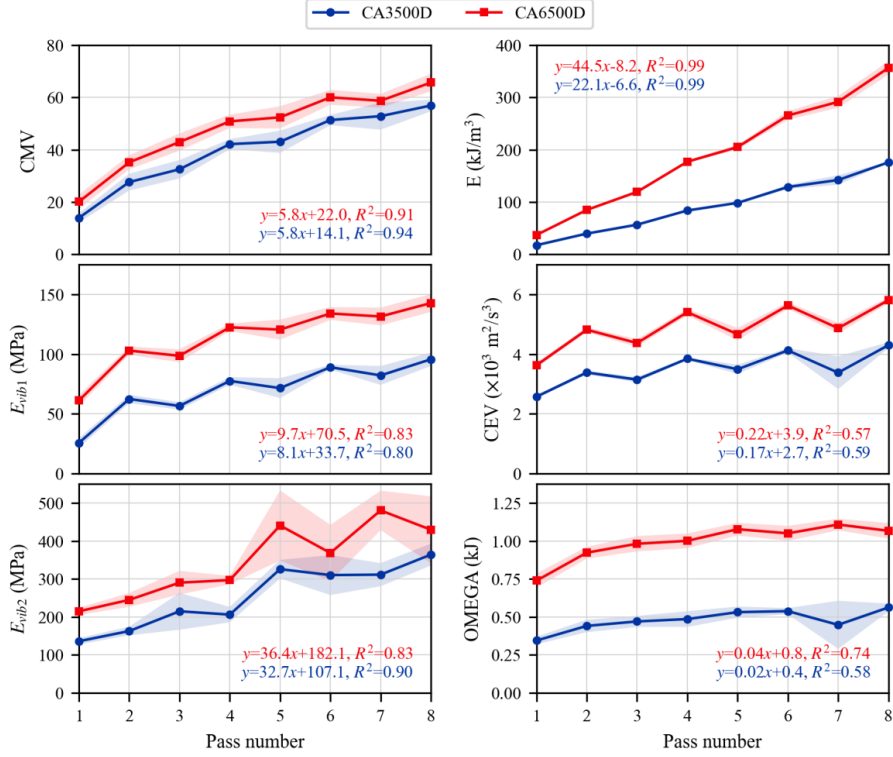


Fig. 6. Variation of selected ICMVs with N .

3.3 Correlations between ICMVs and E_{v2}

Commonly used in practical calibration, simple linear regression between ICMVs and E_{v2} was adopted here to compare the performance of different ICMVs across plate sizes and rollers on a consistent and interpretable basis. The slope reflects the sensitivity of E_{v2} to changes in the ICMV, while the intercept represents the extrapolated initial deformation modulus.

3.3.1 Influence of plate diameter

Fig. 7 presents the correlations between E_{v2} measured with different D and representative ICMVs from each category, with each regression line fitted to 22 paired measurements. For $D = 300 \text{ mm}$, R^2 values are at or below 0.3 across all selected ICMVs. In contrast, the 600-mm plate consistently yields higher R^2 values (0.3–0.5). This improvement can be attributed to its greater measurement depth [52], which better aligns with the rollers' influence depth, attenuates the contribution of stiffer near-surface layers, and averages out local inhomogeneities, resulting in a lower extrapolated initial E_{v2} . The overall weak correlation likely reflects both the limited data range and the contrast between the static, point-based PLT and the dynamic, continuous CCC measurement.

In terms of regression slopes, both CMV and E_{vib1} show larger slopes for the 600-mm plate, while E_{vib2} exhibits the lowest R^2 and a slightly smaller slope for the larger plate. The relatively

similar slopes of E_{vib1} and E_{vib2} across plate sizes suggest that mechanics-based indicators show a more consistent correlation with E_{v2} that is less dependent on plate diameter.

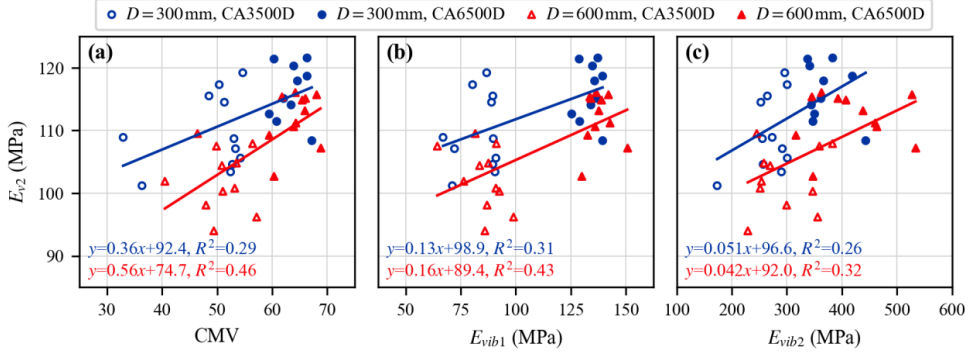


Fig. 7. Correlation between E_{v2} measured with different D and representative ICMVs collected by different rollers at $N=6$: (a) CMV, (b) E_{vib1} , and (c) E_{vib2} .

3.3.2 Influence of roller type

Fig. 8 presents correlations between E_{v2} and the full set of ICMVs for both rollers, using data from $N=2, 4$, and 8 . Four data points for the CA3500D at $N=8$ are missing due to equipment malfunction. The overall ranking of correlation strength was mechanics-based ($R^2 = 0.4\text{--}0.7$) $\geq$ acceleration-based ($R^2 = 0.4\text{--}0.6$) $>$ energy-based ICMVs ($R^2 = 0.2\text{--}0.5$), with a few individual exceptions. The poorest correlations are observed for DMV and CF. DMV yields $R^2 \approx 0$ and is therefore unsuitable as an indicator of ground stiffness. CF is also impractical because of its narrow range. ICMVs derived from common principles, such as the harmonic family (CMV, AICV, CCV, THD) and the stiffness family (k and E_{vib}), exhibit nearly identical scatter patterns and regression statistics.

A closer examination reveals that, compared with CMV, acceleration-based indicators that include more harmonic and sub-harmonic components (e.g., THD and F_t) tend to show better correlations. Since F_t also considers the normalized ratio of the ground contact force to the front module weight, it shows a strong correlation similar to that of mechanics-based indicators. Within the stiffness family, E_{vib1} (k_1) has the strongest correlation with E_{v2} , followed by E_{vib} and E_{vib2} (k_b and k_2). This suggests that the loading segment of the roller response better reflects E_{v2} , which is likewise loading stiffness. The relatively weaker correlation for E_{vib2} may be explained by its larger variability, as shown in **Fig. 6**. Among the energy-based indicators, CEV and OMEGA show two distinct clusters corresponding to the two rollers. Possibly due to its low variability, CEV exhibits the strongest correlation for the CA6500D among all indicators. The relatively poor correlation for OMEGA is likely because the actual soil displacement does not exactly match the drum displacement. Furthermore, partial contact loss [53] becomes more severe as the soil continues to stiffen, resulting in decreased ICMV readings and degraded correlation. As N spans a wide range, E continues to increase almost linearly, whereas E_{v2} grows nonlinearly and eventually levels off, thereby weakening the correlation between them. Additionally, E should be interpreted with caution and regarded as an approximate indicator of the input compaction work, rather than an exact measure of the energy absorbed by the soil.

The linear regression parameters in **Fig. 8** provide further insight into the roller-dependence. Compared to the CA6500D, the CA3500D exhibits a larger slope and a smaller intercept across all indicators, except for a larger intercept on OMEGA. Under the same E_{v2} , the CA3500D tends to produce smaller ICMVs, thereby providing higher sensitivity. For example, as shown in **Fig. 4** and **Fig. 6**, the mean E_{vib1} values for the CA3500D at $N = 4$ and for the CA6500D at $N = 2$ are approximately 75 and 100 MPa, respectively. The smaller intercept is expected because it imparts a lower initial ground stiffness during the preparatory static compaction (when ICMV is theoretically zero).

If the ICMV is interpreted as a proxy for the energy absorbed by the soil, the slope also represents an “energy conversion efficiency”, i.e., the fraction of the compaction energy that effectively increases soil stiffness within the PLT’s measurement depth. The higher and almost doubled energy conversion efficiency of the CA3500D probably results from reduced contact loss and a better match between its influence depth and the PLT. These two factors also explain the stronger correlations observed with the CA3500D. Its lower excitation level reduces contact loss, while the heavier roller introduces more variability, as shown by the wider error bands in **Fig. 6**, which weakens the correlation.

This concept also explains why the dimensionless slope values for E_{vib1} and E_{vib2} are less than 1, and why the slope value for E_{vib2} is much smaller and close to zero, since the unloading phase contributes little to permanent densification. It also explains the observation in **Fig. 7** that the slope value for the plate with $D = 600$ mm is greater than that for the plate with $D = 300$ mm, because the energy absorbed within a larger soil volume is greater.

In summary, mechanics-based ICMVs, particularly E_{vib1} , showed the strongest correlation (R up to 0.8) and a physically interpretable link to E_{v2} , yet remained sensitive to roller-specific parameters. Acceleration-based ICMVs (e.g., the CMV family) offer comparable correlations yet a less direct measure of soil stiffness. Energy-based ICMVs, such as OMEGA and E , are conceptually appealing but perform relatively poorly due to a disconnect between the theoretical energy input and the actual energy mobilized in the ground. These results also highlight the substantial impact of roller characteristics on ICMV measurement and underscore the importance of machine-specific calibration in current CCC practice.

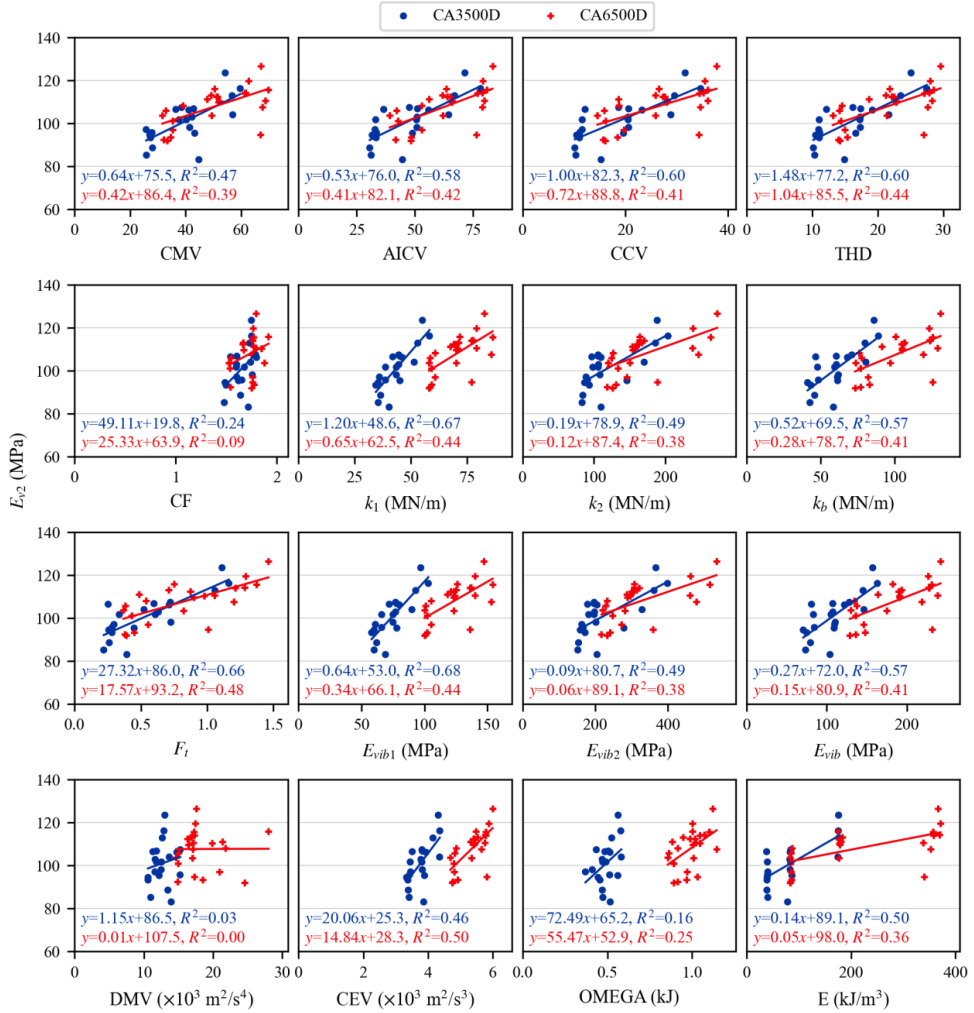


Fig. 8. Correlation between E_{v2} measured by the 600-mm plate and ICMVs collected by different rollers from $N = 2, 4$, and 8.

3.4 Implications for CCC-based QA workflows

This section provides several practical implications for the application of CCC in earthwork quality assurance. First, the results show that a 600-mm PLT plate is preferable for calibration when feasible, because it provides a more reliable correlation with ICMVs under the tested conditions. This is practically important because the objective of calibration is not to maximize the absolute E_{v2} value but to establish a stable and meaningful relationship between the roller response and the accepted QA metric.

Second, the results confirm that machine-specific calibration remains necessary in current practice, and that target ICMV values should not be transferred directly between rollers without accounting for machine dependence.

Third, the study provides a structured strategy for selecting ICMVs from a large and partly redundant set of candidates. Mechanics-based ICMVs should be prioritized, especially the vibration modulus, because they show the strongest physical and statistical link to E_{v2} , balancing dynamic range and stability, while maintaining consistent correlations across plate diameters. A harmonic-based ICMV, such as CMV, may be added as a secondary indicator because it provides comparable correlation while being simple and widely implemented.

Fourth, the results indicate that the number of passes should be selected carefully. Excessive passes should be avoided because they produce only marginal stiffness gain while increasing variability, especially for the heavier roller. Surface loosening should also be addressed to improve compaction uniformity and calibration reliability. From a QA perspective, this means that a stable calibration state should be targeted, rather than simply maximizing the number of passes or the measured ICMV.

Overall, the study advances current practice by clarifying how plate size, roller type, and ICMV choice jointly affect calibration quality. These findings provide a rational pathway toward future machine-independent ICMVs and more reliable, transferable CCC-based QA workflows.

4 Conclusions

This study conducted full-scale vibratory compaction tests on a well-graded gravel to quantify the correlation between E_{v2} and sixteen ICMVs across different plate diameters and rollers. The following key conclusions are drawn:

- PLTs with a 600-mm plate yielded mean E_{v2} values that were 5–7% lower than those obtained with a 300-mm plate, but they produced stronger correlations with ICMVs. For the representative indicators, the corresponding R^2 values increased from about ≤ 0.3 for the smaller plate to 0.3–0.5 for the larger plate. The larger plate is therefore recommended for calibration when feasible.
- The heavier CA6500D roller achieved higher stiffness faster, producing E_{v2} values 7–10% higher than those of the CA3500D at $N = 6$. However, the lighter roller generally yielded stronger correlations and higher sensitivity to ICMV. This confirms that roller-specific calibration remains necessary in current CCC practice.
- Existing ICMVs show substantial redundancy and can be grouped into three distinct clusters. In general, mechanics-based ICMVs performed best, with R^2 values of about 0.4–0.7, followed by acceleration-based ICMVs (0.4–0.6), whereas energy-based ICMVs were generally weaker (0.2–0.5). Among the evaluated indicators, vibration modulus showed the strongest correlation but also a pronounced roller dependence.

The primary challenge in advancing CCC technology is to develop a machine-independent ICMV for universal QA. Future efforts should prioritize indicators with a clear mechanical basis that directly capture roller–soil interaction and the associated energy dissipation mechanisms. One approach is to account for variable drum–soil contact conditions (e.g., contact width [54]) during compaction when computing E_{vib} . Another promising direction is to develop an ML model informed by coupled multibody–finite element simulations of vibratory compaction. Using operating parameters together with curated vibration responses as inputs, such a model may help estimate the compaction effect across a wider range of soil conditions and machine

settings. Further full-scale tests are needed to evaluate how vibration frequency and amplitude affect the ICMV– E_{v2} correlations and their generalizability to other compaction scenarios.

Acknowledgments

This research was financially supported by the Swedish Transport Administration through Better Interaction in Geotechnics (BIG) (Grant No. A2023-06), the Development Fund of the Swedish Construction Industry (SBUF) through Peab Anläggning AB (Grant No. 14198), and Dynapac Compaction Equipment AB. The authors thank Dynapac for providing equipment, personnel, and access to its research facility for the full-scale tests.

Appendix A. Calculation of acceleration-based ICMVs

Time-domain characteristics of the vertical acceleration signal, such as peak value (a_p), root-mean-square value (a_{rms}), and crest factor (CF) [35], can be directly used as ICMVs. For frequency-domain indices, the raw acceleration was band-pass filtered (5–150 Hz) to suppress low-frequency drift and high-frequency noise. The 150 Hz upper cutoff is more than six times the vibration frequency.

The filtered signal was partitioned into equal 1-s segments, and a fast Fourier transform (FFT) was applied to each to obtain amplitude spectra illustrated in **Fig. A.1**. Each segment contains 24 vibration cycles at 24 Hz and covers 1 m at 1 m/s, balancing spectral accuracy and spatial resolution. It is sufficient to resolve local variations [55].

Calculated according to **Eqs. (1)–(5)**, ICMVs used the amplitudes of the fundamental A_ω , higher harmonics ($A_{2\omega}, \dots, A_{6\omega}$), and sub-harmonics ($A_{0.5\omega}, \dots, A_{3.5\omega}$). The scaling constant C was 300 for CMV and AICV, and 100 for CCV and THD. F_t also includes the ratio of the ground contact force F_s to the front module weight $W = (m_d + m_f)g$.

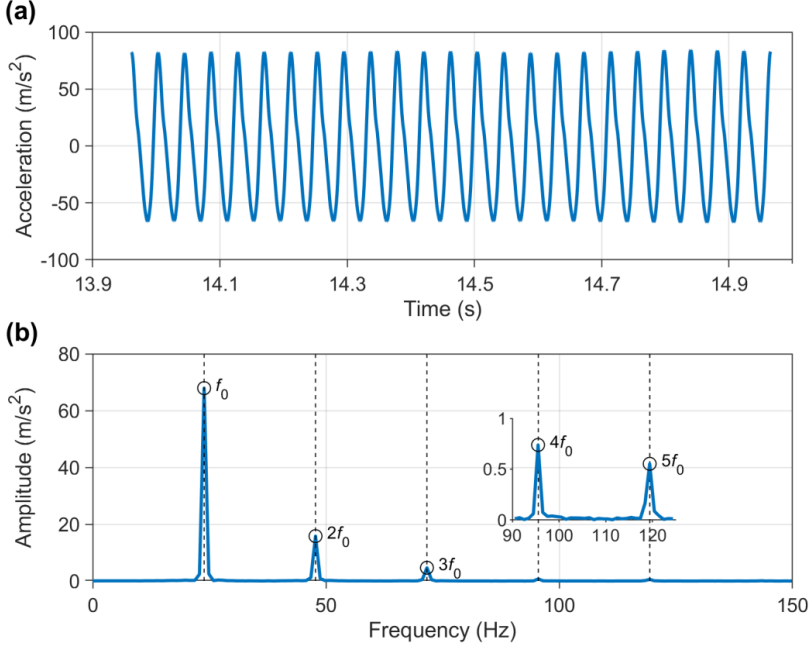


Fig. A.1. Illustrative drum vertical acceleration in: (a) time and (b) frequency domains.

Appendix B. Calculation of mechanics-based ICMVs

The ground reaction force F_s in **Eq. (8-a)** was derived from Newton's second law, as shown in **Eq. (B.1)**. The phase lag between the eccentric force and the measured acceleration was identified through calibration on an air cushion that replicates the operating amplitude and frequency. The time offset Δt was then determined by cross-correlation [56].

$$F_s = m_d \ddot{z} + (m_d + m_f)g - m_0 e_0 \Omega^2 \cos[\Omega(t - \Delta t)] \quad (\text{B.1})$$

where F_s is the ground reaction force, $\ddot{z}$ is the drum vertical acceleration, m_d and m_f are the drum and frame masses, $g = 9.81 \text{ m/s}^2$, m_0 is the eccentric mass, e_0 is the eccentricity, Ω is the angular vibration frequency, t is the elapsed time, and Δt is the calibrated time offset. Note that the equation applies when the accelerometer yields positive values for upward acceleration and assumes $t = 0$ when the eccentric pulse from the position sensor is registered.

Drum vertical displacement Z_d in **Eq. (8-a)** was obtained by double-integrating the filtered acceleration. Based on the F_s – Z_d curve in **Fig. B.1**, different stiffness parameters were calculated using **Eqs. (B.2)–(B.4)**.

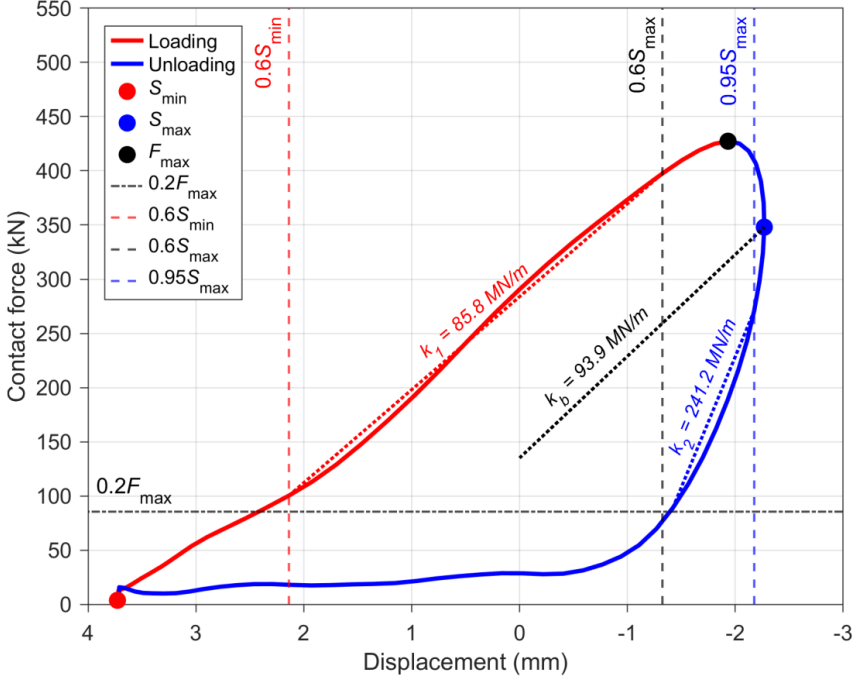


Fig. B.1. Schematic for different stiffness parameters.

$$k_1 = \frac{F_{0.6S_{\max}} - F_{0.6S_{\min}}}{0.6S_{\max} - 0.6S_{\min}} \quad (\text{B.2})$$

$$k_2 = \begin{cases} \frac{F_{0.95S_{\max}} - F_{0.6S_{\max}}}{0.95S_{\max} - 0.6S_{\max}}, & F_{0.6S_{\max}} \geq 0.2F_{\max} \\ \frac{F_{0.95S_{\max}} - 0.2F_{\max}}{0.95S_{\max} - 0.2F_{\max}}, & F_{0.6S_{\max}} < 0.2F_{\max} \end{cases} \quad (\text{B.3})$$

$$k_b = \frac{F_{S_{\max}} - (m_d + m_f)g}{S_{\max}} \quad (\text{B.4})$$

where k_1 and k_2 respectively denote the tangential stiffness during the loading and unloading phases of a vibration cycle, and k_b is the secant stiffness from the static point to the maximum displacement.

The stiffness values are then used to solve for the corresponding vibration moduli (E_{vib1} , E_{vib2} , and E_{vib}) using the relationship in **Eq. (B.5)**, which is derived by combining **Eqs. (7)–(8)**.

$$k = \frac{E_{vib} L \pi}{2(1-v^2) \left(1.8864 + \ln \frac{L}{\sqrt{\frac{16R(1-v^2)F_{\text{stat}}}{E_{vib} L \pi}}} \right)} \quad (\text{B.5})$$

where E_{vib1} , E_{vib2} , and E_{vib} are the vibration moduli for the loading phase, unloading phase, and entire cycle, respectively. F_{stat} is the drum weight, L is the drum width, R is the drum radius, and ν is Poisson's ratio, set at 0.25.

Appendix C. Calculation of energy-based ICMVs

The calculation of DMV is analogous to that of other acceleration-based ICMVs. It is a weighted sum of the energy (squared amplitude) of various frequency components up to 5 times the fundamental frequency ω_0 . The weight decreases for higher frequencies. The frequency resolution was 1 Hz.

To calculate CEV, the vertical acceleration signal was first decomposed into a series of intrinsic mode functions (IMFs) using variational mode decomposition (VMD) [57]. The absolute tolerance, number of IMFs, and penalty factor were set to 1×10^{-6} , 5, and 2000, respectively. The resulting IMFs were then processed with the Hilbert-Huang Transform (HHT), an adaptive algorithm for nonlinear and non-stationary signal processing [58]. The Hilbert spectrum $H(\omega, t)$ was obtained in the time-frequency domain. Integrating this spectrum over time yields the marginal spectrum $h(\omega)$, which represents the energy distribution at different frequencies. The total energy carried by the signal (CEV) was then calculated by integrating $h(\omega)$ over the frequency domain. **Fig. C.1** illustrates the IMFs, Hilbert spectrum, and marginal spectrum of an example acceleration signal.

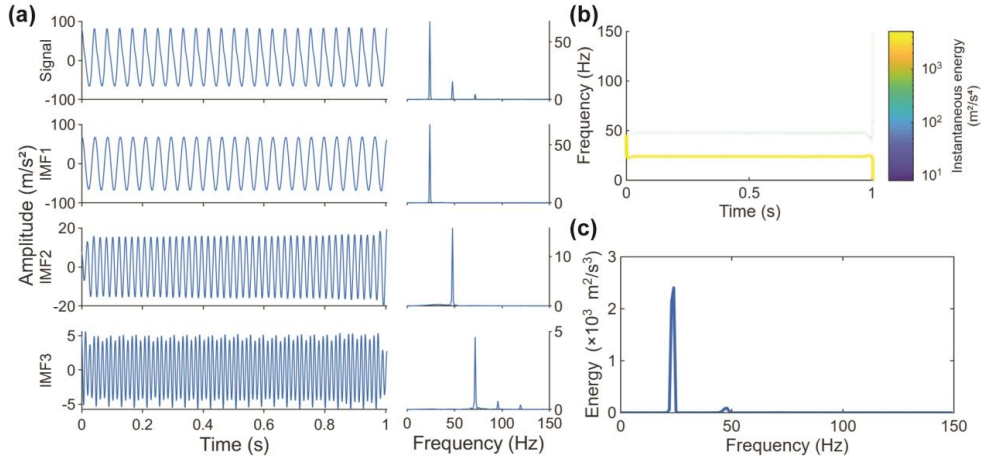


Fig. C.1. Example VMD-HHT results: (a) IMFs and FFT spectra, (b) Hilbert spectrum, and (c) marginal spectrum.

OMEGA was calculated as the area of the force-displacement hysteresis curve for each vibration cycle using trapezoidal integration.

The calculation of E includes the contact force F_s and operational parameters such as vibration amplitude A , frequency f , static weight W , number of passes N , travel speed V , and drum width L . Ideally, the compacted thickness h would be determined from the elevation difference measured before and after compaction. However, such surveying was not feasible within the

scope of the testing program. Therefore, h was assumed to be constant at 0.25 m, based on the average value reported in the original study [50]. A constant h has also been adopted in other studies [59]. Under this assumption, E becomes proportional to the compacting energy per unit area proposed by Sakai [60].

Appendix D. Effect of additional static compaction

The surface loosening effect is well recognized in practice and often necessitates additional static compaction after vibratory compaction is completed [26]. **Fig. D.1** compares scenarios with and without additional static passes following vibratory passes. The results show that the additional static passes increased the average E_{v1} and E_{v2} values by 66.5% and 16.7%, respectively. The average E_{v2}/E_{v1} ratio decreased by 29.9%. This indicates that surface loosening reduces ground stiffness and can lead to an overestimation of residual compaction potential. Additionally, the additional static compaction generally improved the selected ICMV– E_{v2} correlations, as shown in **Fig. D.2**. Without it, the correlations were weaker or might not even exist, as indicated by the negative regression slopes.

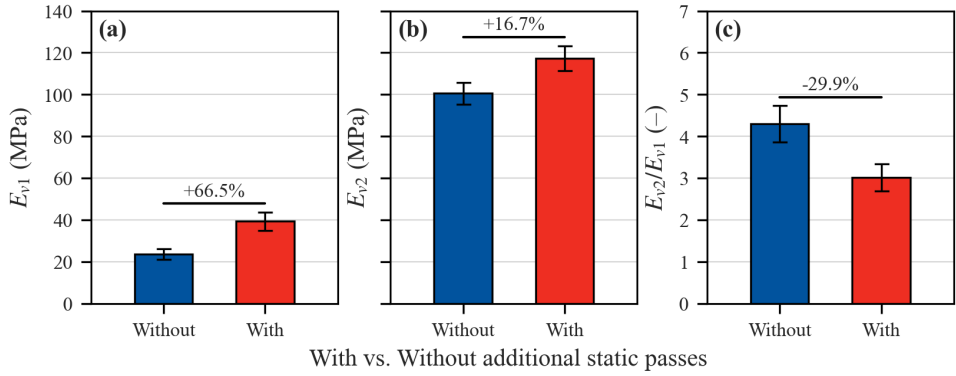


Fig. D.1. Effect of additional static compaction on PLT results: (a) E_{v1} , (b) E_{v2} , and (c) E_{v2}/E_{v1} .

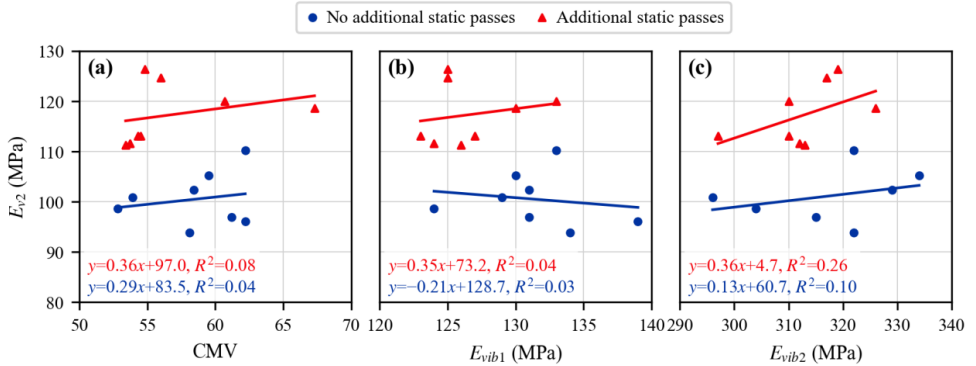


Fig. D.2. Effect of additional static compaction on selected ICMV– E_{v2} correlations: (a) CMV, (b) E_{vib1} , and (c) E_{vib2} .

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Paper B

Nonlinear vibration response of a roller-soil system using finite element analysis with hypoplasticity

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Abstract: The nonlinear vibration response of the coupled roller-soil system remains difficult to interpret because it is governed by soil state, roller properties, operating parameters, and evolving drum-soil contact. This study develops a two-dimensional dynamic finite element model of vibratory compaction to examine the nonlinear vibration response and roller-integrated compaction measurement values (RICMV_s). Four constitutive descriptions are compared under identical operating conditions: linear elasticity, Mohr-Coulomb (MC) plasticity, modified Drucker-Prager/Cap (DPC) plasticity, and hypoplasticity with intergranular strain (Hypo+IGS). The results show that the soil model strongly affects predicted settlement and stress-strain histories. The MC model captures yielding but produces only shear dilation, and the DPC model provides limited volumetric contraction. Hypo+IGS gives the most consistent response across initially loose to dense soil states because it captures void-ratio reduction, density-dependent stiffness, and distinct loading-unloading behavior. The depth of influence depends on the chosen response quantity, ranging from 1.0 to 1.3 m based on settlement and from 1.5 to 2.4 m based on density-related criteria. The vibration moduli, E_{vib1} and E_{vib2} , are more closely related to final-state density measures than CMV and OMEGA. The normalized void-ratio reduction, $(e_0 - e)/(e_0 - e_d)$, yields the most consistent relation across the evaluated ICMV_s. These findings clarify the mechanisms controlling nonlinear roller response and support FEM-based interpretation of continuous compaction measurements.

Keywords: Vibratory compaction, Finite element analysis, Roller-soil dynamic interaction, Hypoplasticity with intergranular strain, Roller-integrated compaction measurement values, Influence depth

1 Introduction

Vibratory compaction is widely used to improve the stiffness and bearing capacity of earthwork materials. During this process, soil particles rearrange under cyclic loads from the vibrating drum, reducing voids and increasing density. The soil response is strongly path-dependent, exhibiting irreversible deformation, variable stiffness during loading, unloading, and reloading, and pressure- and density-dependent behavior [1]. Moreover, the vibration response of the coupled roller-soil system is affected by many factors [2–4], including soil properties (e.g., gradation and water content) and compaction parameters (e.g., roller weight, vibration amplitude, and frequency). However, evaluating the combined influence of these factors solely through field or laboratory experiments is often impractical and costly. Therefore, a reliable numerical model is needed to investigate the vibration response and support improvements in compaction performance.

Existing numerical approaches differ mainly in how they represent the soil domain and drum-soil interaction. They can broadly be classified as lumped-parameter models (LPM) [5,6], continuum-based methods, such as the finite element method (FEM) [1,7], and non-continuum methods, such as the discrete element method (DEM) [8]. LPM is efficient for analyzing roller motion and operating modes, but it cannot resolve the spatial distribution of stress and strain within the compacted layer. DEM can directly describe particle-scale mechanisms, but field-scale applications remain limited by computational cost and the difficulty of calibrating micromechanical parameters. FEM offers a practical compromise between computational efficiency and mechanical detail. It is well-suited for analyzing macroscopic responses, including volumetric deformation, stress transmission, and drum-soil interaction.

A key requirement for such FEM analysis is an appropriate representation of the inherent nonlinear behavior of compacted material. Previous studies have used linear or nonlinear elastic models to investigate the contact force-displacement response of vibrating drums on layered soil systems [9,10] and the depth of influence [11]. While elastic models with varying moduli can reproduce different operating modes of the vibratory roller (e.g., continuous contact, partial uplift, and double jumping) [12], they cannot capture irreversible deformation during compaction. Elastoplastic models such as the Mohr-Coulomb (MC) [13] and modified Drucker-Prager/Cap (DPC) [7,14] better describe shear-induced and pressure-dependent yielding, but they still provide a limited representation of recent strain history and stiffness evolution. A recent bounding surface model improved the prediction of plastic accumulation compared with classical elastoplastic models [15]. However, detailed parameters for other material models were not provided, and the influence of constitutive assumptions on the simulated roller response remains insufficiently clarified. Therefore, an advanced constitutive model capable of capturing nonlinear soil behavior is required for realistic simulation of vibratory compaction.

Beyond material nonlinearity, the loading and boundary conditions introduce additional nonlinearities through the repeated moving load and the evolving drum-soil contact. Some studies [16,17] have idealized roller excitation as a prescribed quasi-static load applied over a given width, without explicitly considering contact between the drum and the soil. However, this assumption limits the ability to reproduce the time-dependent contact force and depth of influence induced by vibratory loading. In many dynamic analyses, the roller is modeled as a single-degree-of-freedom system [9–11,18,19], and the effect of the frame is introduced only through a static surcharge on the drum. Such idealization can significantly affect wave propagation due to inconsistent representations of vibrating mass, stiffness, and damping.

In addition, roller travel and drum rotation are often overlooked, even though these large rigid-body motions alter the contact condition during compaction. Experimental and numerical studies have shown that the drum's stick-slip motion [14,20] and variable contact geometry [21,22] affect the force transferred to the soil. These effects directly influence the simulated surface deformation, stress-strain distribution beneath the drum, and energy transmission. In reality, while the vibrating drum rolls along the soil surface, it produces transient stress waves, hysteretic deformation, and continuously changing contact forces. Therefore, a dynamic FEM analysis that accounts for drum-soil contact, the roller frame's vibrating mass, and the roller travel is necessary to investigate the coupled system's response during continuous compaction.

These modeling issues are directly relevant to roller-integrated compaction measurement values (RICMV), which are used for real-time assessment of compaction quality. RICMVs are calculated from the dynamic response of the roller, such as drum acceleration or contact force-

displacement behavior. Field measurements are indispensable for validation, but they often combine several uncertain factors simultaneously. Numerical simulation can provide cleaner response data under controlled assumptions and is therefore valuable for interpreting and improving RICMVs. Evaluating the evolution of compaction quality requires a constitutive model capable of reproducing irreversible densification under cyclic loading, such as hypoplasticity with intergranular strain (Hypo+IGS) [23,24]. However, few studies have systematically examined the simulated dynamic response and the resulting RICMVs.

To address this gap, this study investigates how soil constitutive assumptions influence the nonlinear response of a vibratory roller-soil system and evaluates the resulting RICMVs. A dynamic FEM model is developed that explicitly considers repeated moving loads, drum-soil contact, roller-frame mass, and cyclic densification. Four constitutive models with increasing complexity, namely linear elastic, MC, DPC, and Hypo+IGS, are compared under identical roller operating conditions and different initial compaction states. The analysis focuses on surface deformation, stress-strain response, contact force-displacement behavior, density evolution, and RICMVs. The results provide insight into the influence of constitutive models on the predicted roller response and offer guidance for interpreting continuous compaction measurements.

2 Finite element model

The FEM model developed in this study is a two-dimensional representation of the roller-soil system, with an out-of-plane thickness equal to the drum width of 2.13 m. The model consists of two parts: the soil medium and the vibratory roller. The roller comprises a vibrating drum, a frame, and a lumped-parameter spring-damper element that represents the vibration-isolation system between the drum and the frame. The full-scale compaction tests reported in a previous study [25] provide the experimental basis for the material properties, roller characteristics, and operating parameters used in this study.

Because vibratory compaction is dominated by vertical excitation and the response is expected to vary mainly in the vertical-longitudinal plane, the system is approximated using a plane-strain model. Previous experimental studies have shown that plane-strain conditions can extend to a depth of 0.5 m beneath the drum [26]. A numerical study has also indicated that plane-strain modeling can provide a sufficiently accurate assessment of the compaction effect [27].

2.1 Soil domain and constitutive models

Fig. 1 illustrates a two-dimensional sketch of the soil medium (subgrade) and the roller model. It is assumed that the subgrade is a homogeneous, isotropic, infinite half-space composed of a single soil layer. The region of interest subjected to compaction is a rectangular finite domain with a length of 12 m and a thickness of 4 m. At its boundaries to the surrounding half-space, which is not significantly affected by the roller, infinite elements [28] with a length of 4 m are used to provide quiet boundaries, absorb propagating waves, and minimize reflections in static and dynamic analyses. The material behavior associated with the infinite elements is linear elastic.

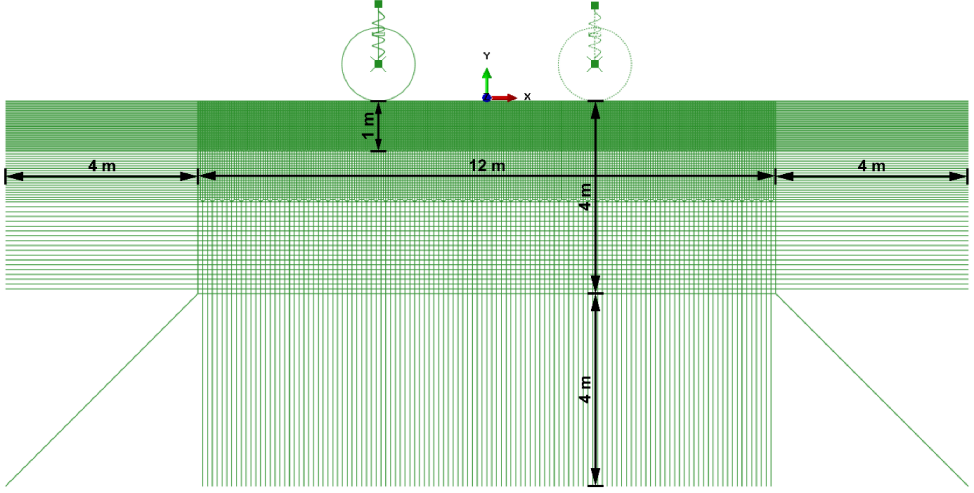


Fig. 1. Sketch of the finite element model and the superimposed mesh.

The soil behavior was described by four constitutive models of increasing complexity: linear elastic, MC plasticity, modified Drucker-Prager/Cap (DPC) plasticity, and Hypo+IGS. The adopted parameters are summarized in **Table 1**.

The linear elastic model was used as a baseline to isolate the influence of stiffness on dynamic response. The MC model represents frictional yielding with a pressure-dependent strength envelope defined by the friction angle φ and cohesion c , while a non-associated flow rule is introduced via the dilatancy angle ψ to avoid unrealistic volumetric expansion under shear.

The DPC model augments the DP shear failure surface with an elliptical cap to represent yielding under hydrostatic compression. The yield surfaces are shown in **Fig. 2**, and the shear failure, cap, and transition surfaces are given in Eqs. (1)–(3) [29], respectively.

$$F_s = t - p \tan \beta - d = 0 \quad (1)$$

$$F_c = \sqrt{(p - p_a)^2 + \left[\frac{Rt}{\left(1 + \alpha \frac{\alpha}{\cos \beta}\right)} \right]^2} - R(d + p_a \tan \beta) = 0 \quad (2)$$

$$F_t = \sqrt{(p - p_a)^2 + \left[t - \left(1 - \frac{\alpha}{\cos \beta}\right)(d + p_a \tan \beta) \right]^2} - \alpha(d + p_a \tan \beta) = 0 \quad (3)$$

$$p_a = \frac{p_b - Rd}{1 + R \tan \beta} \quad (4)$$

$$\varepsilon_v^{pl} = \frac{c_c - c_s}{\ln 10 \cdot (1 + e_0)} \ln \frac{p_b}{p_0} \quad (5)$$

where t is the deviatoric stress measure, p is the mean effective stress, p_a is an evolution parameter that controls the hardening–softening behavior as a function of the volumetric plastic strain ε_v^{pl} , as shown in Eqs. (4) and (5) [30], p_b is the hydrostatic compression yield stress, p_0 is the initial mean effective stress at the geostatic state, R is a shape parameter that controls the cap eccentricity, and α is a small number used to define a smooth transition surface F_t between the shear failure surface F_s and the cap surface F_c .

The friction angle and cohesion (β, d) in the $p - t$ plane are obtained from the parameters (φ, c) by matching the DP cone to the MC surface in triaxial compression according to Eqs. (6) and (7) [31].

$$\tan \beta = \frac{6 \sin \varphi}{(3 - \sin \varphi)} \quad (6)$$

$$d = \frac{6c \cos \varphi}{(3 - \sin \varphi)} \quad (7)$$

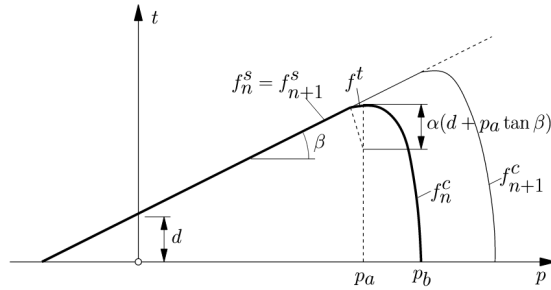


Fig. 2. Yield surfaces of the DPC model in the p - t plane.

Finally, Hypo+IGS is a state-dependent model for granular soils, in which stiffness and dilatancy/contractancy evolve with stress level and void ratio. Unlike elastoplastic models, hypoplasticity does not separate elastic and plastic strain and does not require a yield surface, plastic potential, or flow rule. In general form, the model relates the effective stress rate to the current effective stress, stretching, and void ratio: $\dot{\boldsymbol{\sigma}}' = \mathbf{h}(\boldsymbol{\sigma}', \dot{\boldsymbol{\varepsilon}}, e)$. This model is adopted to account for the key features of granular soil behavior subjected to vibratory compaction: irreversible deformation, path dependence, critical-state behavior, barotropy, and pyknotropy [1]. It also uses the void ratio as a state variable, thereby representing the current density state of the soil. For a detailed description of the constitutive law, the reader is referred to Mašín (2019) [32]. In what follows, a concise account is included.

The influence of mean effective stress and void ratio is considered through Eqs. (8)-(12), and the isotropic compression behavior is described by Eq. (13). The intergranular strain extension introduces an additional internal variable to capture recent strain history, small-strain stiffness, and cyclic hysteresis. In particular, the intergranular strain parameters m_R and m_T control the very-small-strain shear stiffness upon strain-path reversals (180° and 90° , respectively), R defines the size of the quasi-elastic strain range and is usually treated as a material-independent constant [33], and β_r and χ govern the rate of stiffness degradation with increasing strain amplitude. In summary, the hypoplastic model for sand requires eight material parameters

$(\varphi_c, h_s, n, e_{d0}, e_{c0}, e_{i0}, \alpha, \beta)$, and the intergranular strain extension requires five additional parameters $(m_R, m_T, R, \beta_r, \chi)$. The relevant parameters in **Table 1** were adopted from the Hochstetten gravel and the intergranular strain parameters reported for sand [34].

$$\dot{\boldsymbol{\sigma}} = f_b f_e [\hat{a}^2 \dot{\boldsymbol{\varepsilon}} + \hat{\boldsymbol{\sigma}} (\hat{\boldsymbol{\sigma}} : \dot{\boldsymbol{\varepsilon}}) + f_d \hat{a} (\hat{\boldsymbol{\sigma}} + \hat{\boldsymbol{s}}) \|\dot{\boldsymbol{\varepsilon}}\|] \quad (8)$$

$$f_b = \frac{h_s}{n} \left(\frac{1+e_i}{e_i} \right) \left(\frac{e_{i0}}{e_{c0}} \right)^\beta \left(\frac{3p_s}{h_s} \right)^{1-n} \left[3 + a^2 - \sqrt{3}a \left(\frac{e_{i0}-e_{d0}}{e_{c0}-e_{d0}} \right) \right]^{-1} \quad (9)$$

$$f_d = \left[\frac{(e-e_d)}{(e_c-e_d)} \right]^\alpha \quad (10)$$

$$f_e = \left(\frac{e_c}{e} \right)^\beta \quad (11)$$

$$a = \frac{\sqrt{3}(3-\sin \varphi_c)}{2\sqrt{2} \sin \varphi_c} \quad (12)$$

$$\frac{e_i}{e_{i0}} = \frac{e_c}{e_{c0}} = \frac{e_d}{e_{d0}} = \exp \left[- \left(\frac{p_s}{h_s} \right)^n \right] \quad (13)$$

where f_b is the barotropy factor, f_d and f_e are the pyknotropy factors, e_{d0} , e_{i0} , and e_{c0} are the void ratios at the densest, the critical, and the loosest states, h_s is the granular hardness, n is an exponent constant that controls the decrease of the limiting void ratios with increasing pressure during isotropic compression, α and β are exponent constants that describe the influence of the relative void ratio on the peak friction angle and on the stiffness, respectively. a is a parameter that depends on the critical friction angle φ_c .

Additionally, to prevent individual nodes at the free surface from experiencing excessive tensile strains that can lead to loss of material stiffness and, consequently, termination of the analysis, the apparent cohesion associated with the Hypo+IGS model was set to 5 kN/m². A “protective foil” [27] was also applied by assigning a linear elastic constitutive law to the first row of soil elements, with an E value of 20 MPa determined by trial and error.

This study concerns the compaction of well-graded gravel, and the influence of water content is beyond its scope. Initial compaction states were represented differently depending on the constitutive formulation. For the Elastic, MC, and DPC simulations, six elastic modulus levels ($E = 10, 20, 40, 60, 80$, and 100 MPa) were prescribed. For the Hypo+IGS simulations, nine initial void ratios, $e_0 = 0.476, 0.452, 0.428, 0.404, 0.380, 0.356, 0.332, 0.308$, and 0.284 , were used, corresponding to initial relative densities $D_{r0} = 10\%, 20\%, 30\%, 40\%, 50\%, 60\%, 70\%, 80\%$, and 90% . For the DPC model, three cap radii ($R = 0.3, 0.5$, and 0.7) were additionally considered to examine different volumetric responses. Unless otherwise stated, comparisons among the four constitutive models were made using the reference parameter set $E = 40$ MPa for the Elastic, MC, and DPC models, $R = 0.5$ for the DPC model, and $D_{r0} = 50\%$ for the Hypo+IGS model.

Because the models were not calibrated against a single common material dataset, their results are used for qualitative and mechanistic comparison rather than direct quantitative ranking. Although the Elastic, MC, and DPC models shared the same elastic modulus settings and the

DPC strength parameters were converted from the MC parameters, they differ in their assumptions for yielding, plastic flow, volumetric behavior, and hardening.

Table 1 Material parameters for the constitutive models used in the reference case.

Model	Parameter	Symbol	Value	Unit
Elastic	Density	ρ	2200	kg/m ³
	Young's modulus	E	40	MPa
	Poisson's ratio	ν	0.3	—
MC	Friction angle	φ	35	°
	Cohesion	c	1	kPa
	Dilation angle	ψ	5	°
DPC	Friction angle	β	54.8	°
	Cohesion	d	2.0	kPa
	Cap eccentricity	R	0.5	—
	Transition surface radius	a	0.01	—
	Flow stress ratio	K	0.778	—
	Compression index	C_c	0.01	—
	Swelling index	C_s	0.001	—
	Initial hydrostatic compression yield stress	p_{b0}	20	kPa
Hypo+IGS	Critical friction angle	φ_c	36	°
	Granulate hardness	h_s	32	GPa
	Pressure exponent for limiting void ratios	n	0.18	—
	Minimum void ratio at zero pressure	e_{d0}	0.26	—
	Critical void ratio at zero pressure	e_{c0}	0.45	—
	Maximum void ratio at zero pressure	e_{i0}	0.50	—
	Density exponent for peak friction	α	0.10	—
	Density exponent for stiffness	β	1.9	—
	IGS stiffness factor for 180° strain-path reversal	m_R	5	—
	IGS stiffness factor for 90° strain-path change	m_T	2	—
	Intergranular strain radius	R	1×10^{-4}	—
	IGS evolution exponent	β_r	0.5	—
	IGS evolution exponent	χ	6	—

2.2 Vibratory roller model

Table 2 presents the relevant parameters of the Dynapac CA3500D and CA6500D single-drum vibratory rollers considered in this study. They correspond to the two machines used in the reference tests [25], with static linear loads of 35 kg/cm and 65 kg/cm, respectively. Since the main focus of this study is the soil, and the stress distribution on the drum surface is not of primary interest, the drum is modeled as an analytical rigid body. The corresponding masses were assigned to the reference points RP_D at the drum center and to RP_F for the front frame. The mechanical properties of the isolation system between the drum and the front frame are described by an equivalent linear spring-dashpot element, as shown in **Fig. 1**. The spring and dashpot elements are defined between RP_D and RP_F along the vertical direction, and the spring stiffness and dashpot coefficient are given in **Table 2**. The vibratory frequency and travel speed are set to $f = 24$ Hz and $v = 1$ m/s for both rollers, following the operating conditions in [25].

Table 2 Parameters of the vibratory rollers used in the simulations.

Parameter	Symbol	Value		Unit
		CA3500D	CA6500D	
Drum mass	m_d	4040	5300	kg
Frame mass	m_f	3565	8470	kg
Drum width	W	2.13	2.13	m
Drum diameter	D	1.518	1.546	m
Eccentric moment	$m_0 r_0$	7.31	10.31	kg·m
Isolation stiffness	k_d	1.27×10^6	3.01×10^6	N/m
Isolation damping	c_d	2.07×10^4	4.12×10^4	kg/s

2.3 Numerical implementation

2.3.1 Drum-soil contact

Surface-to-surface contact with finite sliding in ABAQUS/Standard was used to model the interaction between the drum's outer surface and the subgrade surface at $y=0$ over the range $-2.5 \leq x \leq 2.5$ m. The drum-soil contact was represented by a classical isotropic Coulomb friction law, given the limited experimental characterization of the actual contact behavior. Shear stress can develop up to the critical frictional traction (stick), after which sliding occurs (slip). The friction coefficient is $\mu = 0.3$, and the normal behavior follows a hard contact formulation with separation (uplift) permitted.

2.3.2 Analysis steps and loading conditions

The analysis was performed in five steps: Initial, Geoini, Seating, Loading, and Compaction. In the Geoini step, gravity was applied to the soil to equilibrate the imposed in-situ stress state (K_0 procedure) established in the Initial step. The drum, with its center at $(x, y) = (-2.25, 0)$, was then seated by prescribing a 5 mm downward displacement at RP_D to establish drum-soil contact. The static axle load P (drum and frame weights) was subsequently applied at RP_D , as shown in Eq. (14). In the dynamic compaction step, forward motion was imposed by prescribing the horizontal velocity $v(t)$ at both RP_D and RP_F , ramped over the acceleration period $t_{acc} = 0.5$ s to reach the target speed $v = 1$ m/s. A downward sinusoidal excitation force $F(t)$ was applied at RP_D , as shown in Eq. (15). To mitigate impact-induced numerical oscillations, the excitation was introduced using the same ramp function given in Eq. (16) for the vibration frequency f during t_{acc} . After the acceleration phase, the excitation became fully harmonic, and the roller continued at constant speed for an additional 4 s. For brevity, this paper mainly presents the results of the compaction step.

$$P = (m_d + m_f)g \quad (14)$$

$$F(t) = m_0 r_0 (2\pi f)^2 \sin(2\pi f t) \quad (15)$$

$$a(t) = \begin{cases} A\xi^3(10 - 15\xi + 6\xi^2), & 0 \leq t < t_{acc} \\ A, & t \geq t_{acc} \end{cases} \quad \text{where } \xi = \frac{t}{t_{acc}} \quad (16)$$

2.3.3 Spatial and temporal discretization

The spatial discretization of the soil domain was designed to satisfy both dynamic wave-propagation and contact-resolution requirements. To adequately resolve up to the fifth harmonic of the operating frequency ($f_{\max} = 120$ Hz), the maximum element size in the far field was limited to one-tenth of the shear wavelength ($h_{\max} \leq \lambda_{\min}/10$). In addition, capturing the steep deformation gradients beneath the drum demanded a finer mesh in the near-field contact zone. Accordingly, the mesh was designed to place at least ten elements across the drum–soil contact width, which measures approximately 0.3 m at a travel speed of approximately 1 m/s [22].

The domain was discretized using four-node bilinear plane strain quadrilateral elements (CPE4) with a graded mesh. A highly refined grid of $0.025 \text{ m} \times 0.025 \text{ m}$ was applied in the surficial layer ($-1 \text{ m} \leq y \leq 0 \text{ m}$). The mesh was coarsened smoothly with depth to $0.05 \text{ m} \times 0.05 \text{ m}$ ($-2 \text{ m} \leq y \leq -1 \text{ m}$) and $0.1 \text{ m} \times 0.1 \text{ m}$ ($-4 \text{ m} \leq y \leq -2 \text{ m}$) to optimize computational efficiency. This transition was achieved using trapezoidal elements with a minimum interior angle of 45° and an aspect ratio of 1:2. To minimize the artificial reflection of compression and shear waves back into the domain, infinite elements (CINPE4) providing velocity-proportional damping were applied to the semi-infinite boundaries. The final discretized model comprises 27,404 elements.

The dynamic boundary-value problem was solved implicitly using ABAQUS/Standard (version R2025). In the compaction step, time integration was performed using the Hilber-Hughes-Taylor (HHT) algorithm, with the numerical damping parameter set to $\alpha = -1/3$ to maximize dissipation of high-frequency noise. The half-increment residual check was disabled to improve solution efficiency. A maximum time increment of $\Delta t_{\max} = 2 \times 10^{-4} \text{ s}$ was prescribed, guaranteeing a high temporal resolution of more than 200 steps per vibration cycle. Using the Hypo+IGS material model, simulating a single roller pass (from $x = -2.25 \text{ m}$ to $x = 2.0 \text{ m}$ over 4.5 s) required approximately seven days of computation on a single AMD EPYC 7742 cluster core.

2.3.4 Damping and numerical stability

To improve convergence in the static analyses (specifically, the Seating and Loading steps), adaptive automatic stabilization was enabled using a dissipated energy fraction of 2×10^{-5} . The resulting stabilization energy ALLSD remained much smaller than the internal energy ALLIE (ALLSD/ALLIE $\ll 1\%$), indicating that the added numerical damping was negligible and did not materially affect the final equilibrium solution.

Rayleigh damping was introduced to phenomenologically approximate energy dissipation (e.g., material hysteresis, friction, radiation) and to stabilize numerical noise in dynamic FEM analysis. The Rayleigh damping coefficients were computed using a target damping ratio $\zeta = 5\%$ at the target frequencies $f_1 = 24 \text{ Hz}$ and $f_2 = 120 \text{ Hz}$ using Eqs. (17) and (18), giving $\alpha = 12.57$ and $\beta = 1.11 \times 10^{-4}$.

$$\alpha = \frac{2\zeta\omega_1\omega_n}{\omega_1 + \omega_n} \quad (17)$$

$$\beta = \frac{2\zeta}{\omega_1 + \omega_n} \quad (18)$$

where α and β are the mass-proportional and stiffness-proportional damping coefficients, respectively.

Note that Rayleigh damping is not a material damping law in the constitutive sense but should be viewed as numerical viscous damping. The actual material damping in the developed FEM model originates from plasticity (hysteretic damping) and contact (frictional damping).

3 Results

3.1 Surface deformation

As shown in **Fig. 3**, the static axle load of the CA3500D roller produced a localized and nearly symmetric settlement zone beneath the drum. However, the spatial extent of settlement differed markedly among the constitutive models. For the initially medium-dense soil modeled with Hypo+IGS, the maximum settlement was approximately 10.4 mm.

During vibratory compaction, as shown in **Fig. 4**, the settlement field became asymmetric with respect to the drum, with a pronounced settlement trough developing mainly beneath and behind the drum and an upward displacement zone, or bow wave [35,36], appearing ahead of it. When the drum rolled over $x = 0$, the maximum settlement predicted by Hypo+IGS reached approximately 96.6 mm, which was substantially larger than that obtained under the axle load.

The comparison between **Figs. 3** and **4** demonstrates that the vibration response cannot be represented by the static axle load alone. The large settlement predicted by Hypo+IGS indicates that the model can capture the gradual compaction caused by repeated contact loading and unloading. By contrast, the elastic model recovered most of the deformation after unloading and therefore underestimated settlement. Although the MC and DPC models produced residual settlement after yielding, they showed different magnitudes and deformation patterns because of their different plastic flow rules and hardening assumptions.

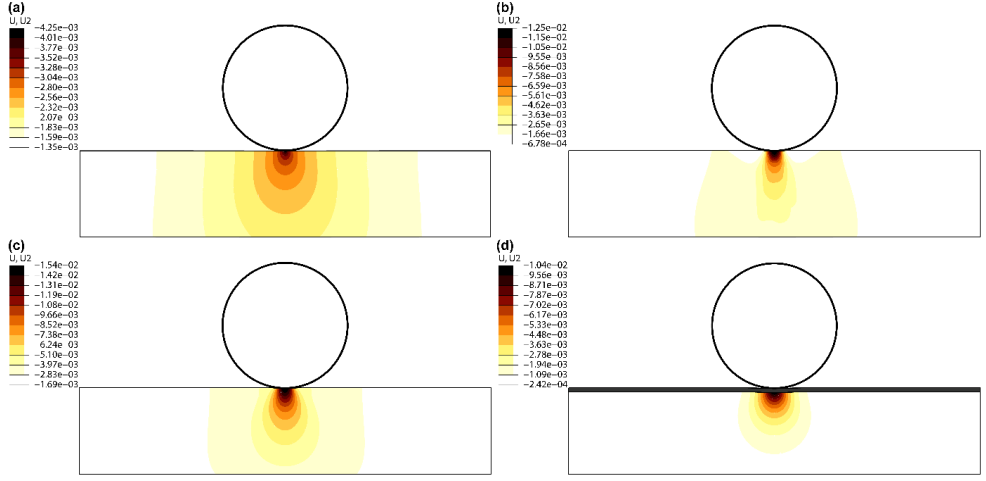


Fig. 3. Vertical displacement contours after applying static axle load for (a) Elastic, (b) MC, (c) DPC, and (d) Hypo+IGS models.

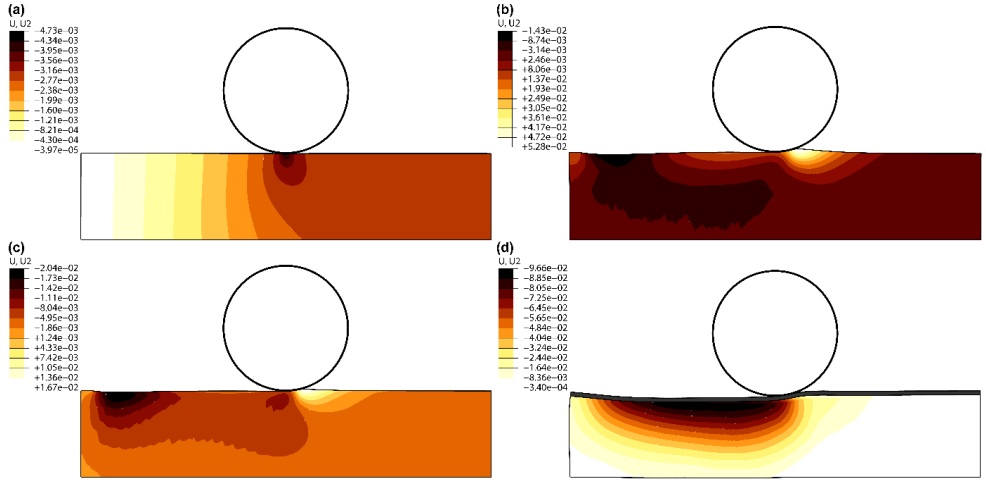


Fig. 4. Vertical displacement contours when the vibrating drum rolled over $x = 0$ for (a) Elastic, (b) MC, (c) DPC, and (d) Hypo+IGS models.

3.2 Stress and strain responses at different depths

Figs. 5-8 present selected stress and strain responses along a vertical profile located at $x = 0$, at depths $y = -0.125, -0.25, -0.5$, and -1 m. The horizontal coordinate X denotes the relative position of the moving drum with respect to this profile. Thus, $X < 0$ corresponds to the approaching stage, $X = 0$ indicates that the drum center is above the profile, and $X > 0$ represents the departing stage. The selected stress responses are the vertical stress σ_{yy} and shear stress σ_{xy} , while the selected strain responses are the vertical strain ϵ_{yy} and volumetric strain ϵ_v . Compressive normal stresses are negative, and negative volumetric strain denotes contraction.

The stress response shows a clear depth dependence for all constitutive models. The largest vertical compressive stress σ_{yy} occurs in the upper soil layer and decreases with depth, as shown in **Fig. 5**. For Hypo+IGS, the peak σ_{yy} decreases from about -187 kPa at $y = -0.125$ m to about -64 kPa at $y = -1$ m. Similar attenuation is observed for the mean pressure p and the von Mises stress q . The elastic model produces the smoothest and most symmetric stress distributions, with peak stress occurring when the drum is nearly above the profile, followed by rapid recovery after the drum passes. In contrast, the MC, DPC, and Hypo+IGS models exhibit more asymmetric stress histories, with peak p , q , and σ_{yy} occurring slightly before $X = 0$, typically around $X = -0.1$ to -0.3 m, indicating a phase shift between the moving drum load and the soil stress response.

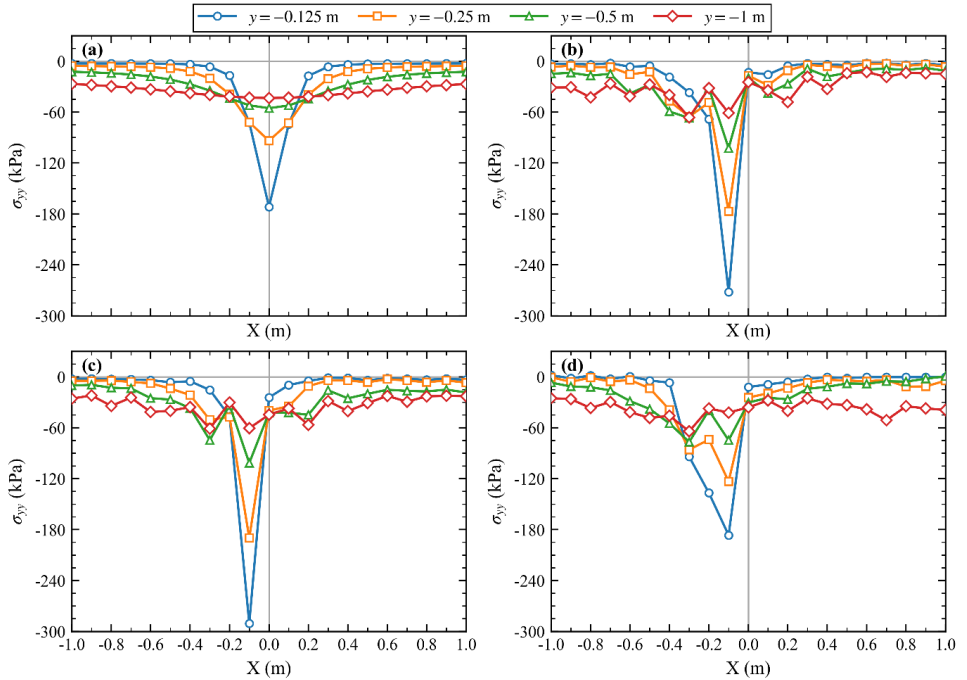


Fig. 5. Vertical stress σ_{yy} along $x = 0$ at different depths for (a) Elastic, (b) MC, (c) DPC, and (d) Hypo+IGS models.

The σ_{xy} changes sign as the drum passes the profile, as shown in **Fig. 6**. This sign reversal reflects the change in shear direction between the approaching and departing stages. The elastic model shows an antisymmetric pattern, whereas the elastoplastic and hypoplastic models exhibit more irregular response histories due to nonlinear soil behavior and evolving contact conditions. Although σ_{xy} attenuates with depth, the sign reversal remains visible at $y = -1$ m, showing that the moving drum produces a transient shear field over a considerable depth.

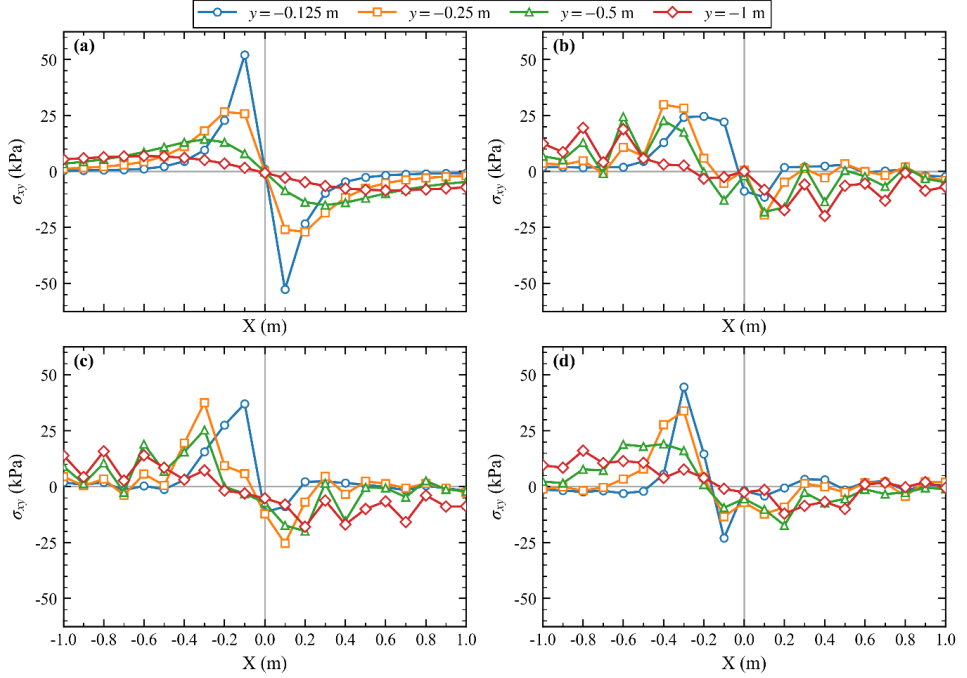


Fig. 6. Shear stress σ_{xy} along $x = 0$ at different depths for (a) Elastic, (b) MC, (c) DPC, and (d) Hypo+IGS models.

The strain response is more sensitive to the constitutive model than the stress response, as shown in **Figs. 7** and **8**. In the MC model, the ε_{yy} and ε_v become positive in the upper layer after the drum passes, indicating a dilative response. The DPC model produces much smaller ε_v , with weak contraction during the approaching stage and partial recovery afterward. By contrast, Hypo+IGS predicts persistent contractive ε_v at all investigated depths. The final ε_v reaches approximately -0.085 to -0.094 in the upper 0.5 m and remains about -0.037 at $y = -1$ m. This indicates that Hypo+IGS captures cumulative densification under cyclic loading, whereas MC mainly produces shear-induced dilation and DPC gives only limited volumetric compaction in the present case.

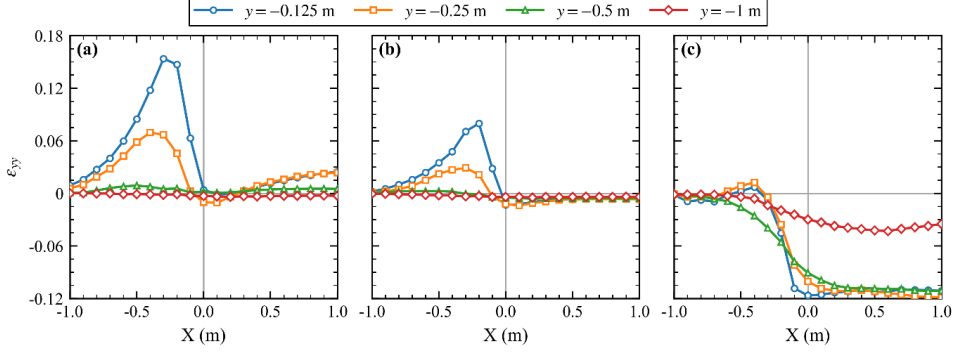


Fig. 7. Vertical strain ε_{yy} along $x = 0$ at different depths for (a) MC, (b) DPC, and (c) Hypo+IGS models.

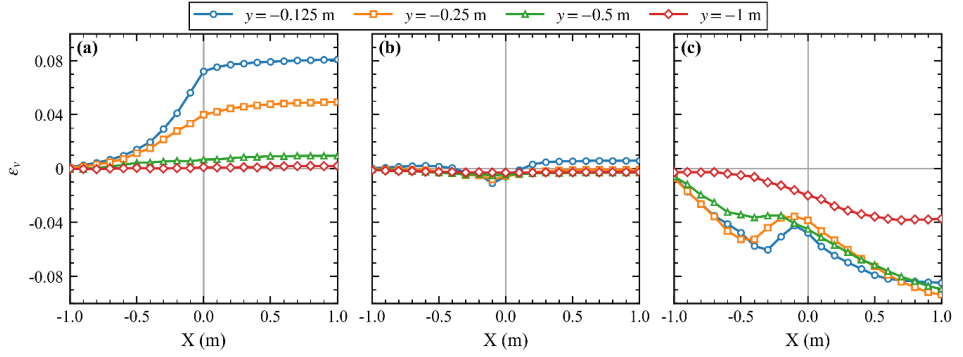


Fig. 8. Volumetric strain ε_v along $x = 0$ at different depths for (a) MC, (b) DPC, and (c) Hypo+IGS models.

The horizontal and shear strain components provide additional insight into the deformation mechanism. The horizontal strain ε_{xx} changes from compression during the approaching stage to extension after the drum passes, especially in the upper 0.25 m. The shear strain γ shows stronger model dependence: MC produces the largest positive residual γ , DPC gives a smaller but similar pattern, whereas Hypo+IGS shows a depth-dependent response with shear direction reversal near the surface and at $y = -1$ m.

3.3 Volumetric plastic strains and void-ratio evolution

The spatial distribution of volumetric plastic strain in **Fig. 9** confirms the different volumetric response mechanisms implied by the constitutive models. The MC model mainly produced positive volumetric plastic strain, with local values reaching about 9.5×10^{-2} , indicating that irreversible deformation was dominated by shear-induced dilation rather than densification. The DPC model, in contrast, produced a narrow zone of contractive volumetric plastic strain beneath the drum through the cap mechanism, with a local minimum of about -6.6×10^{-3} . However, this

contractive zone was surrounded by a much larger shallow region of positive volumetric plastic strain, with a maximum magnitude comparable to that of the MC model. This confirms that compression plasticity was relatively weak under the present conditions and that the shallow deformation field remained strongly affected by dilation.

In the Hypo+IGS model, densification is evaluated directly from the evolving void ratio and relative density, since hypoplasticity does not decompose the total strain into elastic and plastic components. **Fig. 9(c)** shows that the relative density increased locally from the initial value of 0.5 to about 0.85-0.88. The densified zone extended beneath the roller path, indicating cumulative contractive deformation caused by the repeated moving load.

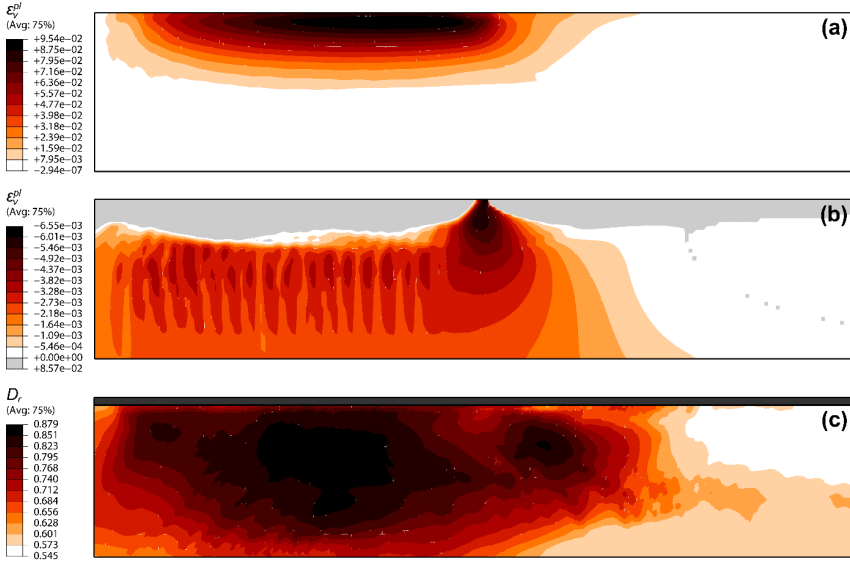


Fig. 9. Volumetric plastic strain contours for the (a) MC and (b) DPC models, and the relative density contour for the (c) Hypo+IGS model, when the drum rolled over $x = 0$.

The depth profiles in **Fig. 10** further show how this densification depends on the initial soil state and roller type. For loose to medium-dense initial states, both rollers produced a positive relative void-ratio reduction, $(e_0 - e)/e_0$, over a substantial part of the upper layer. For the lighter CA3500D roller, the maximum reduction reached about 0.3 for $D_{r0} = 10\%$, while it was about 0.2 for $D_{r0} = 50\%$. For $D_{r0} = 90\%$, the uppermost approximately 0.1-0.2 m showed negative values, indicating local loosening. Below this shallow zone, the reduction became positive and reached about 0.13 at 0.5 m. These results show that incremental densification decreased as D_{r0} increased.

The two rollers also differed in the depth distribution of densification. The lighter CA3500D roller produced its strongest reduction mainly within the upper 0.5-1.0 m, whereas the heavier CA6500D roller distributed the reduction more deeply, with clear changes still visible around 1.0 m. For example, for $D_{r0} = 50\%$, the reduction for the lighter roller was about 0.2 in the upper 0.1-0.5 m and about 0.13 at 1.0 m, while the corresponding values for the heavier roller were about 0.11 near 0.1 m, 0.16 at 0.5 m, and 0.17 at 1.0 m.

Fig. 11 complements this interpretation by showing the remaining compaction potential $(e - e_d)/(e_i - e_d)$. This quantity decreases as the material approaches the densest reference state at zero pressure. Loose initial states retain a high remaining potential after one pass, particularly below the main compacted zone. Dense initial states approach zero in parts of the upper layer and may become slightly negative where the final void ratio falls below the reference value. Compared with the lighter roller, the heavier roller reduces the remaining potential over a greater depth, confirming that it shifts part of the compaction effect from the surface to deeper soil layers.

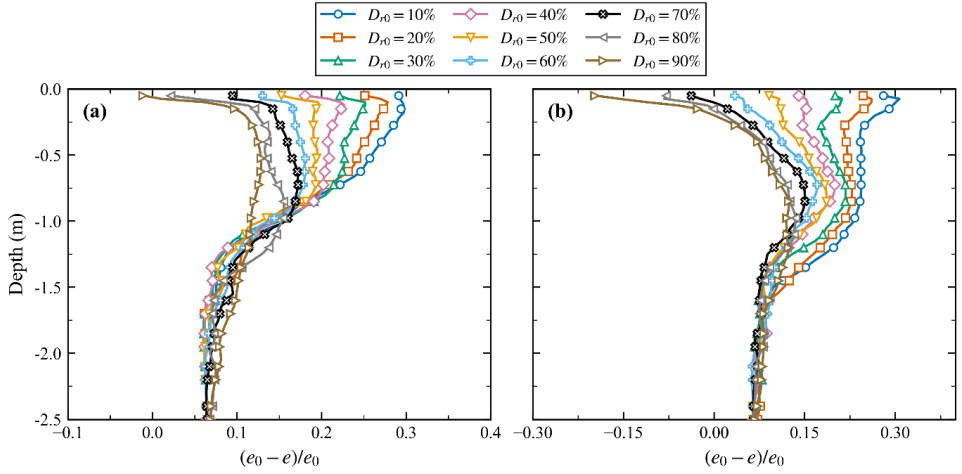


Fig. 10. Relative void ratio reduction along $x = 0$ after compaction for different D_{r0} values simulated with the Hypo+IGS model: (a) CA3500D and (b) CA6500D.

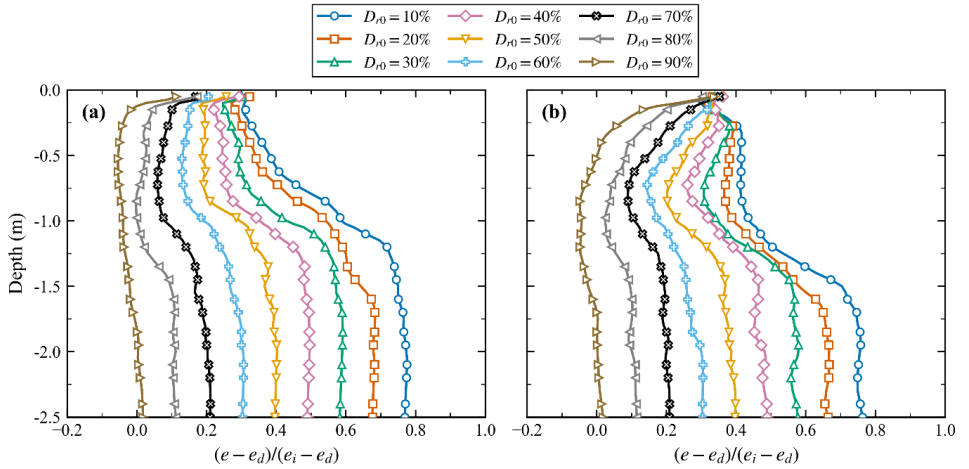


Fig. 11. Remaining compaction potential along $x = 0$ after compaction for different D_{r0} values simulated with the Hypo+IGS model: (a) CA3500D and (b) CA6500D.

3.4 Roller-integrated compaction measurement values

This section evaluates how the density evolution described above is reflected in RICMVs. These indicators are inferred from the dynamic response of the coupled roller-soil system. The compaction meter value (CMV) [37] was calculated from the frequency content of the vertical drum acceleration using the Fast Fourier Transform. The vibration moduli for the loading and unloading phases, E_{vib1} and E_{vib2} [38], were obtained from the drum's contact force-displacement response. The energy index OMEGA [39] was calculated as the area enclosed by the force-displacement loop in each vibration cycle.

The acceleration response in **Fig. 12** shows clear fundamental and second-harmonic components at approximately 24 Hz and 48 Hz, respectively, and their amplitudes increased with increasing D_{r0} . The increase in CMV was nonlinear over the investigated density range. CMV remained relatively low, around 3-4, for $D_{r0} = 10\%$ -60%, then rose rapidly for $D_{r0} \geq 70\%$, reaching approximately 17 at $D_{r0} = 90\%$. This indicates that CMV is particularly sensitive to the onset of stronger contact nonlinearity and harmonic distortion in denser states.

The simulated CMV values at high D_{r0} were lower than those typically measured in the field. This was mainly because partial drum uplift was not pronounced under the present parameter settings, as indicated by the positive contact force throughout the cycles in **Fig. 13(a)**, which limited the second-harmonic content of the acceleration response. The relatively large Rayleigh damping adopted in the simulations may also have attenuated the higher-frequency components. Nevertheless, the simulated CMV range is consistent with the full-scale test results [25] after one vibrated pass and comparable to values reported in previous numerical studies [18] using linear elastic models. This indicates that the model captures a reasonable level of harmonic response under the present conditions.

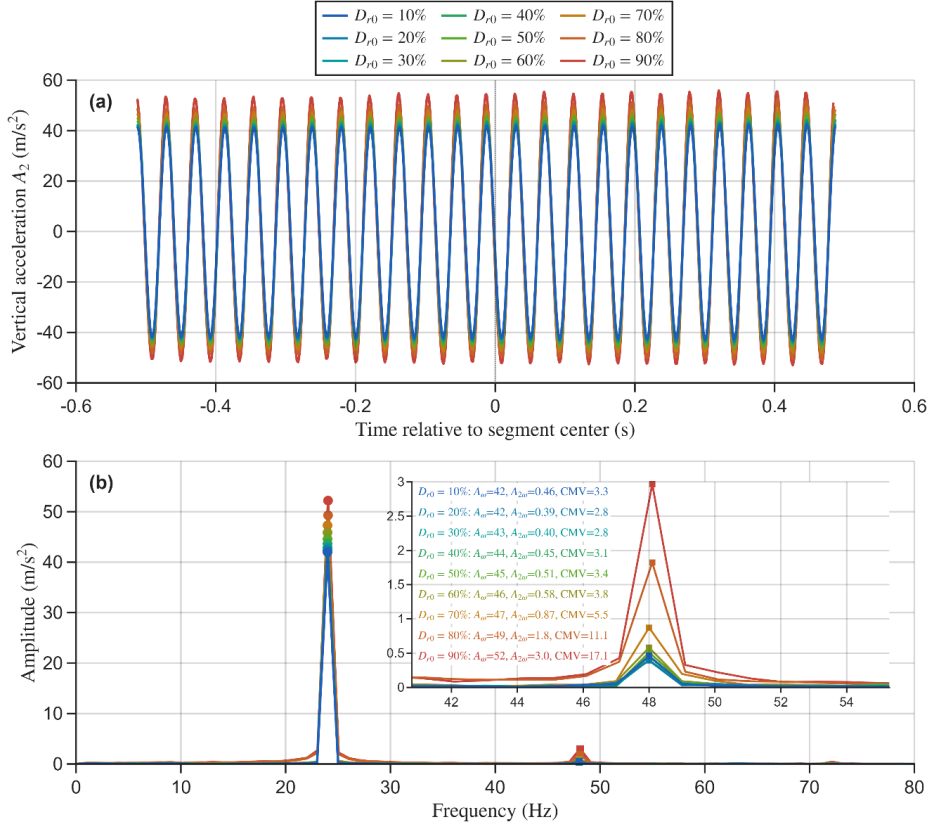


Fig. 12. Vertical drum acceleration response of the CA3500D roller for different D_{r0} values simulated with the Hypo+IGS model: (a) time histories and (b) frequency spectra.

The contact force-displacement loops in **Fig. 13(a)** show the corresponding change in the mechanical response of the roller-soil system. For loose to medium-dense states, the loops have similar shapes and relatively limited changes in inclination, indicating a comparatively soft response. As D_{r0} increases, the loops become steeper and the peak contact force increases, especially for $D_{r0} = 80\%$ and 90% . This reflects the higher dynamic stiffness of the soil and stronger force transfer between the drum and the ground. The loop area also increased, indicating that the work exchanged during each vibration cycle increased with density.

As shown in **Fig. 13(b)**, E_{vib1} increased from about 13 MPa at $D_{r0} = 10\%$ to about 47 MPa at $D_{r0} = 90\%$, while E_{vib2} increased from about 45 MPa to about 126 MPa. E_{vib2} was consistently larger than E_{vib1} , as expected due to compaction during the preceding loading phase and consistent with the full-scale test results [25]. The separation between E_{vib1} and E_{vib2} also confirms that the response is path-dependent.

The energy-related quantity OMEGA followed a similar trend, increasing from approximately 193 J at $D_{r0} = 10\%$ to about 328 J at $D_{r0} = 90\%$. However, its increase became pronounced mainly at higher densities, similar to CMV. This suggests that both CMV and OMEGA are

strongly affected by changes in the dynamic contact condition, whereas E_{vib} provides a more direct measure of the stiffness associated with denser soil states.

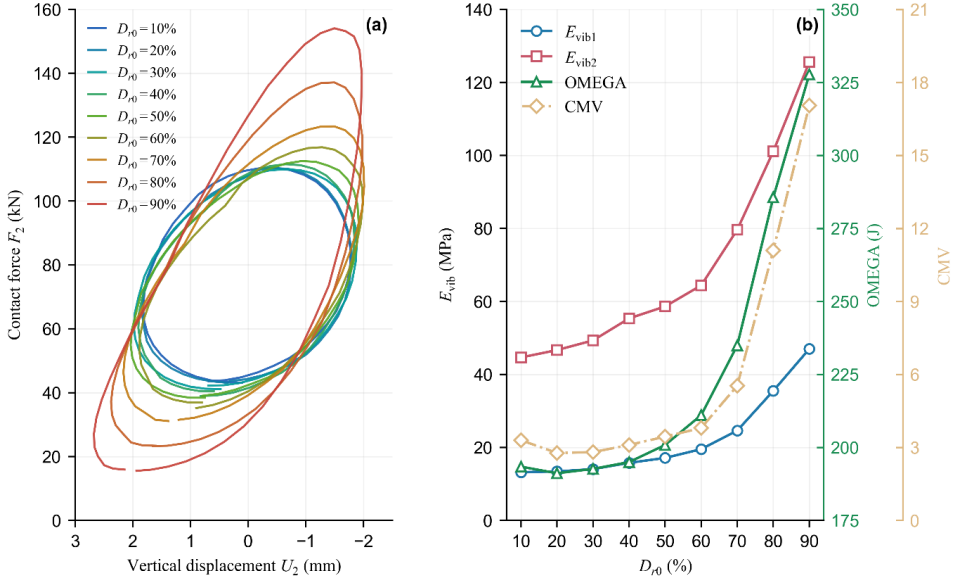


Fig. 13. Contact force-displacement response and average RICMV values for the CA3500D roller simulated with the Hypo+IGS model: (a) hysteresis loops at different D_{r0} values and (b) variation of E_{vib1} , E_{vib2} , OMEGA, and CMV with D_{r0} .

4 Discussion

4.1 Depth of influence

The depth of influence describes the vertical zone in which the soil response is measurably affected by roller compaction. This depth is important for interpreting roller-integrated compaction measurements because RICMVs and spot-test results, such as the deformation modulus from static plate load tests, may represent different measurement volumes. If the two measurements mobilize different depth intervals, their correlation may be affected by differences in measurement depth rather than by compaction quality alone.

Previous studies have commonly defined the influence depth as the depth at which the roller-induced response decreases to 10% of its peak value [11,40]. This study adopts the same criterion but applies it separately to each response quantity. Specifically, the response was calculated as the change from the pre-compaction reference state to the post-compaction state, and the influence depth was defined as the deepest depth at which the response remained above 10% of its peak value.

As summarized in **Table 3**, displacement-, strain-, and density-based criteria can yield different influence depths. The displacement-based depth, obtained from u_2 , is the shallowest, ranging from 1.02 to 1.29 m. The strain-based depth, represented by ε_{yy} , extends deeper, from 1.43 to 2.02 m. The criteria based on void ratio e and relative void ratio $(1+e_d)/(1+e)$ give the largest and nearly identical depths, from 1.49 to 2.39 m. This indicates that permanent densification extends to greater depths than suggested by the settlement response alone.

The results also show systematic effects of roller size and initial density. The heavier roller generally produces a larger influence depth than the lighter one, and the influence depth tends to increase with D_{r0} , especially for the strain- and density-based criteria. Therefore, when RICMV's are compared with composite or depth-averaged spot-test measurements, the effective depth of the spot test should be checked against the compaction influence depth.

Table 3. Influence depths determined from different response-based criteria (m).

Quantity	Roller	D_{r0}		
		20%	50%	80%
u_2	CA3500D	1.02	1.03	1.27
	CA6500D	1.24	1.25	1.29
ε_{yy}	CA3500D	1.43	1.54	1.73
	CA6500D	1.55	1.64	2.02
e	CA3500D	1.50	1.60	2.19
	CA6500D	1.65	1.94	2.39
$(1+e_d)/(1+e)$	CA3500D	1.49	1.59	2.18
	CA6500D	1.64	1.93	2.39

4.2 Relationship between RICMV's and relative densities

CMV, E_{vib1} , E_{vib2} , and OMEGA were compared with void-ratio-based quantities averaged over the depth interval affected by compaction, as shown in **Fig. 14**. Three averaging depths, $H = 1.0, 1.5$, and 2.0 m, were examined to reflect the range of influence depths identified in Section 4.1. Four depth-averaged state variables were used to separate the final compacted state from the density change produced during the pass. The average void ratio, e , and the relative density measure, $(1+e_d)/(1+e)$, describe the final soil state after compaction. In contrast, $(e_0-e)/e_0$ describes the relative reduction in void ratio from the initial state, while $(e_0-e)/(e_0-e_d)$ normalizes this reduction by the available compaction potential. Because the relationships are not strictly linear, variable-specific empirical fits were used: exponential decay for e , exponential growth for $(1+e_d)/(1+e)$, hyperbolic decay for $(e_0-e)/e_0$, and linear for $(e_0-e)/(e_0-e_d)$.

Fig. 14 shows that, for the CA3500D roller, the correlations between E_{vib1} or E_{vib2} and the average e were higher than those for CMV and OMEGA. A similar trend was observed for $(1+e_d)/(1+e)$. These results indicate that E_{vib} reflects the stiffness associated with the achieved compaction more consistently. Changing H from 1.0 to 2.0 m resulted in only small variations in R^2 , suggesting that the final compacted state was consistently captured across the investigated depth range.

The correlation with $(e_0 - e)/e_0$ was generally weaker and more dependent on the RICMV. It was also more sensitive to the averaging depth because the density increment is distributed unevenly with depth. The weaker correlation with $(e_0 - e)/e_0$ reflects the mismatch between density increment and current stiffness: initially loose soil undergoes a large void-ratio reduction while remaining soft after one pass, whereas dense soil shows minimal reduction but produces high dynamic stiffness. Therefore, RICMVs should be interpreted primarily as indicators of the current compacted state.

When the reduction was normalized by the initially available compaction potential, $(e_0 - e)/(e_0 - e_d)$, the relationship was the most consistent across all RICMVs, with $R^2 = 0.92$ – 0.97 . This suggests that the normalized mobilization of compaction potential provides a compact way to relate roller response to densification progress and reduces ambiguity caused by the choice of averaging depth.

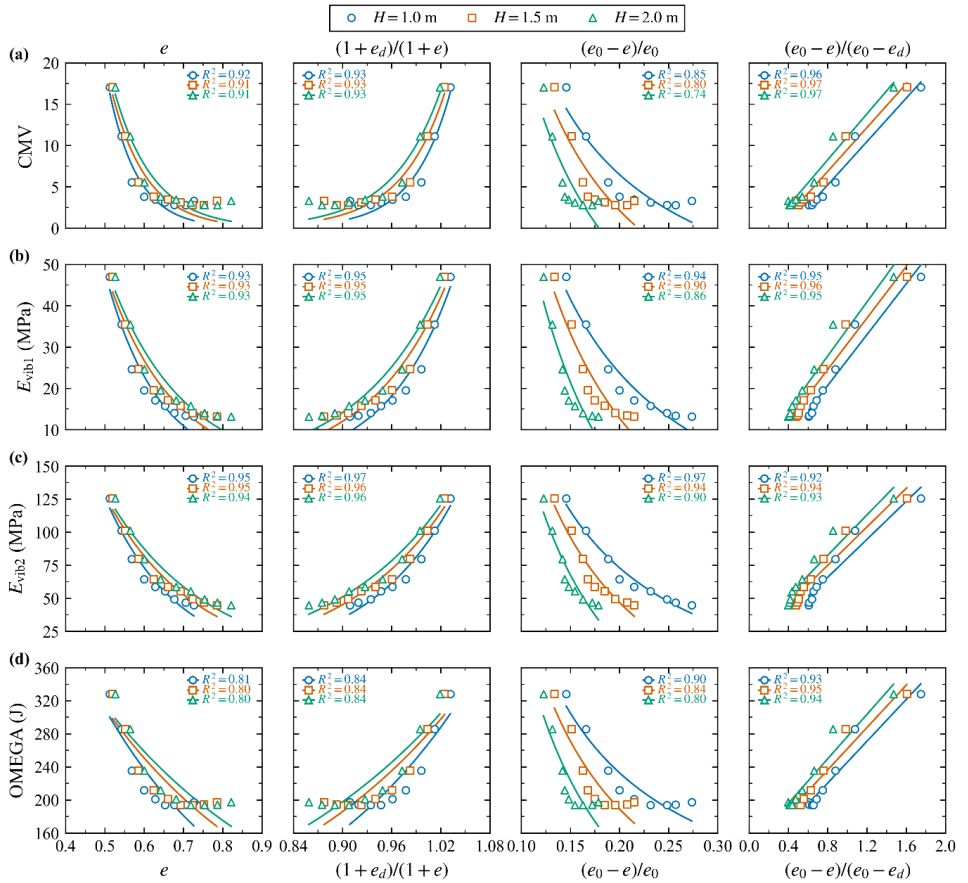


Fig. 14. Relationships between depth-averaged relative void ratios and RICMVs for the CA3500D roller: rows show (a) CMV, (b) E_{vib1} , (c) E_{vib2} , and (d) OMEGA; columns show e ,

$(e_0 - e)/e_0$, $(1 + e_d)/(1 + e)$, and $(e_0 - e)/(e_0 - e_d)$. Results are shown for averaging depths $H = 1.0, 1.5$, and 2.0 m. The curves denote variable-specific empirical fits.

4.3 Role of soil constitutive models

The constitutive model determines which aspects of the compaction process can be represented in the simulation. A linear elastic model is suitable for studying wave propagation and the response of already compacted ground, but it cannot predict permanent settlement. The MC model provides a simple representation of shear yielding, but it is insufficient for soil densification. The DPC model is more appropriate when volumetric compression and cap hardening are important. However, in the present simulations, its contractive zone was limited, and it did not fully reproduce path-dependent stiffness.

Hypo+IGS provides the most complete description for the present problem because it couples stress level, void ratio, recent strain history, and small-strain stiffness. It directly updates soil density and captures persistent contractive volumetric strain, void-ratio reduction, stiffness evolution, and separate loading and unloading responses. This makes it better suited for simulating the compaction of granular material and evaluating residual compaction potential. The cost is a substantial increase in calibration effort, convergence sensitivity, and computational time.

The practical choice of model should therefore depend on the purpose of the analysis. Elastic models may be sufficient for preliminary studies. MC can be used for simple yielding, but it should not be used when the objective is to predict densification. DPC is useful when compression plasticity is needed at a moderate cost. Hypo+IGS should be used when the objective is to predict soil densification, stiffness evolution, residual compaction potential, and RICMVs that depend on the loading-unloading path.

5 Conclusions

This study develops a two-dimensional dynamic FEM model of a vibratory roller operating on granular soil and compares four soil constitutive models to examine vibration response under different initial soil states. The main conclusions are as follows.

- Dynamic FEM analysis is necessary for compaction control because roller response is governed by repeated moving loads and continuously changing drum-soil contact conditions. Vibratory compaction produces an asymmetric settlement trough behind the drum and a bow wave ahead of it, responses that cannot be captured by considering the static axle load alone.
- The elastic model mainly reflects an instantaneous and reversible response and therefore cannot capture the hysteretic nature of vibratory compaction. The MC model produces plastic yielding but mainly shows shear-induced dilation. The DPC model represents compression plasticity, but the predicted contractive zone was limited.
- Hypo+IGS provides the most physically consistent response for initially loose to dense gravel. It captures contractive volumetric strain, density increase, and stiffness

evolution. For looser initial states, the relative void-ratio reduction $(e_0 - e)/e_0$ reaches about 0.3 in the upper layer.

- The depth of influence depends strongly on the chosen criterion. The displacement-based depth is 1.0-1.3 m, the strain-based depth is 1.4-2.0 m, and the density-based depth is 1.5-2.4 m. The heavier roller generally produces a larger influence depth than the lighter roller. Compaction influence should therefore be defined using the response quantity relevant to the measurement being interpreted.
- E_{vib1} and E_{vib2} are more closely related to the final-state density measures than CMV and OMEGA. The normalized void-ratio reduction $(e_0 - e)/(e_0 - e_d)$, which represents the mobilized portion of the initially available compaction potential, shows the most consistent relationship with the RICMV, with R^2 values up to 0.97.

The developed model can be used in future work to evaluate compaction parameters, such as vibration frequency, amplitude, roller mass, and travel speed, as well as residual compaction potential after varying numbers of passes. The next step is to validate the simulated stress-strain response, density profile, and RICMV against instrumented field measurements before applying the model to broader parametric studies of compaction efficiency.

Acknowledgements

The work was financially supported by the Swedish Transport Administration through Better Interaction in Geotechnics (BIG) (Grant No. A2023-06) and by the Development Fund of the Swedish Construction Industry (SBUF) through Peab Anläggning AB (Grant No. 14198). The computations were enabled by resources provided by the National Academic Infrastructure for Supercomputing in Sweden (NAISS). Special thanks to Dynapac Compaction Equipment AB for valuable technical insights and discussions.

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Paper C

Compaction Quality Assessment Based on Machine Learning with Small Datasets

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Abstract. Current practices in compaction quality assessment rely heavily on traditional spot tests, such as the static plate load test (PLT), which are labor-intensive, time-consuming, and limited in spatial coverage. This study develops a machine-learning framework to estimate deformation moduli from continuous compaction measurements. A small dataset of 60 samples from full-scale trials was used to train multi-output regression models, with deformation moduli from the first and second loading cycles (E_{v1} and E_{v2}) as the targets. Two feature representations were compared: a five-feature set of selected intelligent compaction measurement values (ICMVs) and an eight-feature set of curated vibration response characteristics extracted from acceleration signals and contact force–displacement curves. Six algorithms were evaluated, including multiple linear regression, random forest, XGBoost, support vector regression, k -nearest neighbors, and the tabular foundation model TabPFN. The results show that curated response characteristics improved E_{v2} prediction relative to the selected ICMV feature set. For Feature Set 1, SVR achieved the best E_{v2} prediction with $R^2 = 0.34$ and RMSE = 7.1 MPa. For Feature Set 2, TabPFN achieved the best E_{v2} prediction with $R^2 = 0.45$ and RMSE = 6.5 MPa, despite requiring no hyperparameter tuning. The simultaneous prediction of E_{v1} and E_{v2} enabled estimation of the E_{v2}/E_{v1} ratio, with the lowest RMSE = 0.34 achieved by SVR on Feature Set 2. SHAP analysis indicated that second-harmonic acceleration amplitude, loading and unloading stiffness, and displacement amplitude were key features, providing physical interpretability for the data-driven assessment.

Keywords: Vibratory compaction, Intelligent compaction measurement value, Plate load test, Deformation modulus, TabPFN, SHAP analysis.

1 Introduction

Ensuring compaction quality is essential for the stiffness, bearing capacity, and durability of transportation infrastructure, such as road and railway embankments. Quality control/quality assurance (QC/QA) of soil compaction has traditionally relied on index properties, such as density and moisture content. However, mechanistic–empirical (M-E) pavement and geotechnical design increasingly requires perfor-

mance-based properties, such as modulus and stiffness, because these properties are more directly linked to the structural response of the constructed facility. Transitioning from index-property control to performance-based QC/QA can therefore improve alignment among construction assessment, design assumptions, and long-term performance requirements.

In practice, compaction quality assessment still predominantly relies on traditional spot tests, such as the sand cone test, the lightweight deflectometer, and the static plate load test (PLT). These methods are labor-intensive, time-consuming, sensitive to local variability, and assess only a limited portion of the compacted area. For example, as few as five or eight PLT measurements may be performed over a construction area exceeding 5000 m² [1]. Such sparse sampling provides limited information about spatial variability and introduces significant uncertainty when the results are used to represent the condition of the entire compacted layer.

Intelligent compaction (IC) technology has emerged as a promising alternative to increase spatial coverage and reduce the risk of under- and over-compaction [2]. IC-equipped rollers are instrumented with accelerometers that continuously record the drum's vibration response during compaction. From these acceleration signals, various intelligent compaction measurement values (ICMV_s) [2] can be derived and used as indicators of compaction quality, such as the compaction meter value (CMV) and the vibration modulus (E_{vib}). While ICMV_s are generally correlated with soil stiffness, the relationship is highly nonlinear and influenced by material properties [3], roller characteristics [4], and operating parameters, including vibration amplitude and frequency [5] and travel speed [6], making accurate assessment challenging.

Machine learning (ML) provides a data-driven approach to leveraging multivariate information in compaction data without requiring an explicit mechanistic model of drum–soil interaction. Recent studies have demonstrated the potential of ML for compaction quality assessment [7, 8]. However, most existing ML-based compaction research focuses on predicting density or the degree of compaction, whereas comparatively few target the fundamental mechanical properties required for M-E design, such as the deformation modulus from PLT. In addition, uncertainties associated with field trials and limited data availability, often manifested as small sample sizes, can reduce the reliability of reference measurements and, consequently, limit the robustness and generalizability of ML models.

This paper presents a comparative ML study to estimate the deformation moduli from the first and second loading phases (E_{v1} and E_{v2}) using two distinct feature sets. Six algorithms were evaluated, and feature importance was assessed with SHAP values. A key advantage of this study is the use of data from full-scale laboratory tests, which reduces environmental variability and enables a substantial number of PLTs. This provides a robust basis for estimating E_{v1} and E_{v2} . Another practical value of this study is its ability to estimate the E_{v2}/E_{v1} ratio across the site using compaction data, which is a measure of residual compaction potential that has received limited attention.

2 Experimental Program

This study uses the full-scale test data reported in a previous study [4] and focuses on a new ML-based estimation of deformation moduli. Readers are referred to [4] for details of the experimental program, ICMV calculation, and measurement results.

2.1 Full-Scale Trials

Full-scale compaction trials were conducted in an indoor testing facility. The test bed consisted of a 1 m thick layer of well-graded gravel underlain by well-compacted rockfill. Two Dynapac single-drum vibratory rollers with different operating weights were used: the CA3500D (medium class) and the CA6500D (heavy class). The laboratory environment reduced uncertainties typically associated with moisture variations and weather fluctuations under field conditions. During testing, the rollers completed 2–8 successive vibratory passes along the test lanes while continuously recording drum acceleration.

2.2 Plate Load Tests

A PLT [9] provides deformation moduli from the first and second loading cycles, denoted E_{v1} and E_{v2} , respectively. The E_{v2}/E_{v1} ratio can serve as an indicator of residual compaction potential. A lower ratio indicates that a substantial portion of achievable compaction has already occurred under the applied compaction effort, leaving limited potential for further compaction. A total of 116 PLTs were conducted after varying numbers of vibratory passes. Of these, 60 measurements obtained with the same plate diameter and under consistent soil conditions were retained for this study to ensure comparable deformation moduli across samples. The target variables E_{v1} and E_{v2} were then used for the multi-output regression task.

2.3 Intelligent Compaction Measurement Values

Various ICMVs were computed from the drum acceleration signals and used as input features for the ML models. These ICMVs characterize the drum–soil interaction from complementary perspectives and can be grouped into three physical categories:

- The acceleration-based ICMV considered in this study is the turbulence factor (F_t), a variant of CMV that quantifies the severity of nonlinear harmonics in the drum motion.
- The mechanics-based ICMVs include roller-integrated stiffnesses (k_1 and k_2) and vibration moduli (E_{vib1} and E_{vib2}), which reflect the ground stiffness mobilized during loading and unloading.
- The energy-based ICMVs include the area enclosed by the contact force–displacement curve (OMEGA), which quantifies energy transmission from the drum to the soil, and the compaction energy value (CEV).

3 Machine Learning Framework

3.1 Feature Extraction

The ML workflow primarily comprises feature extraction, model training, predictive assessment, and sensitivity analysis. To evaluate the optimal representation of drum–soil interaction for ML, two distinct feature sets were constructed. The 60 samples were partitioned into a training set (80%, 48 samples) and a test set (20%, 12 samples).

Feature Set 1 (selected ICMVs): Initially, 16 ICMVs were computed. Because many ICMVs are highly multicollinear [4, 10], a compact final set was selected to retain representative information while reducing redundancy through correlation analysis. ICMVs with low Spearman correlation coefficients with E_{v2} were excluded. The final feature set consists of F_t , CEV, E_{vib1} , E_{vib2} , and OMEGA, combining harmonic content, vibration modulus, and compaction energy. The correlation heatmap shown in **Fig. 1** confirms that these features are strongly related to the targets, with darker colors indicating stronger correlation.

Feature Set 2 (curated vibration response characteristics): Rather than relying on predefined ICMV formulas, the characteristics were extracted from acceleration signals and contact force–displacement curves. The final feature set consists of A_1 , A_2 , v_{max} , z_d , k_1 , k_2 , $E_{loading}$, and $E_{unloading}$, combining descriptors of acceleration, velocity, displacement, loading and unloading stiffness, and the energy transmitted to and returned from the soil. Their physical meaning is illustrated in **Fig. 2**. Here, v_{max} denotes the drum’s maximum upward velocity, occurring near the transition from soil penetration to rebound when the vertical acceleration crosses zero. The difference $E_{loading} - E_{unloading}$ equals OMEGA.

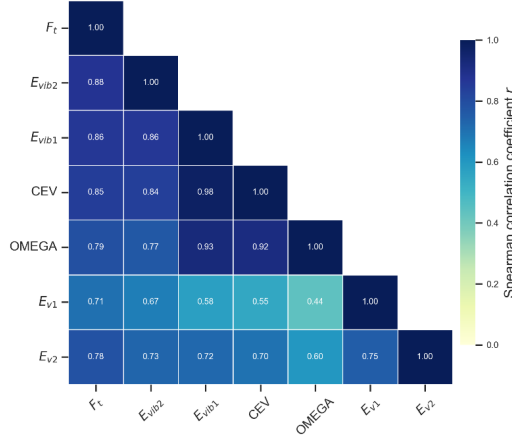


Fig. 1. Correlation heatmap for Feature Set 1 and target variables.

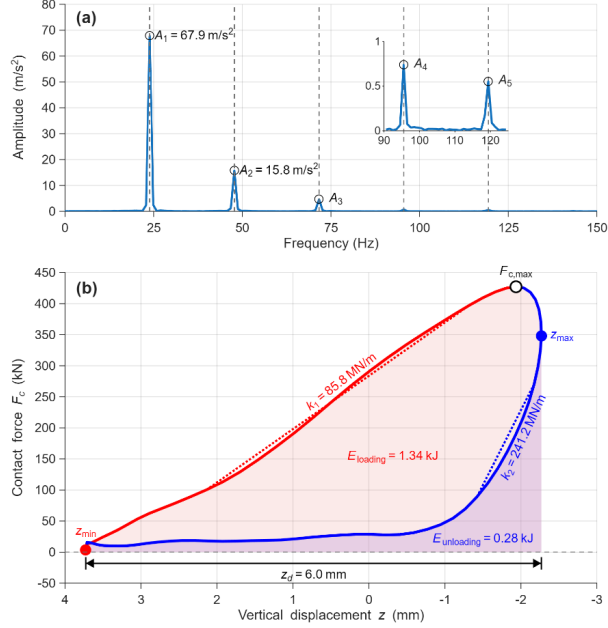


Fig. 2. Response characteristics from (a) the frequency spectrum of drum vertical acceleration and (b) the contact force–displacement curve during a vibration cycle.

3.2 ML Algorithms

Six regression algorithms were evaluated for the multi-output task. They were selected to cover a range of model classes, which allows the available dataset to be assessed using both a transparent baseline and more flexible nonlinear models.

- Multiple linear regression (MLR): a linear baseline used to assess whether nonlinear algorithms are warranted.
- Random forest (RF) [11]: a tree-ensemble method that captures nonlinearity and feature interactions by combining multiple decision trees.
- Extreme gradient boosting (XGBoost) [12]: a gradient-boosted tree method with regularization, which can improve predictive performance while reducing the risk of overfitting.
- Support vector regression (SVR) [13]: a kernel-based method using a radial basis function (RBF) kernel to capture nonlinear relationships.
- k -nearest neighbors (KNN) [14]: a distance-based instance-learning method that predicts target values by averaging the response of the k nearest training samples in Euclidean feature space.

- TabPFN [15]: a transformer-based foundation model for tabular data. Pre-trained on millions of synthetic datasets, TabPFN performs prediction without task-specific hyperparameter tuning, which is advantageous for small datasets where tuning may itself lead to overfitting.

3.3 Model Evaluation

Model performance on the test set was evaluated using the coefficient of determination (R^2) and the root-mean-square error (RMSE, in MPa). Bayesian hyperparameter [16] optimization with 15 iterations and 5-fold cross-validation (CV) was applied to RF, XGBoost, SVR, and KNN. MLR and TabPFN were fitted without hyperparameter search. In addition, repeated 5-fold CV with 10 repeats was performed on the training set to assess stability. Metrics were reported separately for E_{v1} and E_{v2} . At the same time, repeated CV R^2 was computed as the target-averaged R^2 for each validation fold and reported as the mean $\pm$ standard deviation over all folds and repeats. The E_{v2}/E_{v1} ratio was computed from the predicted moduli. Finally, Shapley additive explanations (SHAP) [17] values were computed for the primary target, E_{v2} , to quantify each input feature’s contribution to the model predictions.

4 Results and Discussion

4.1 Predictive Performance of Different Models

Table 1 summarizes the training, test, and repeated CV performance across models. **Fig. 3** also shows the actual-versus-predicted plots for Feature Set 2. The models were evaluated using R^2 and RMSE. Most models exhibit a noticeable gap between training and test performance, indicating that overfitting remains a major challenge for this small dataset. Negative R^2 values indicate that MLR generally failed to capture the nonlinear nature of drum–soil interaction. RF and XGBoost showed strong training performance, but their test performance was lower, reflecting the sensitivity of tree ensembles to limited samples even after Bayesian optimization. SVR generalized more consistently, likely because its regularized formulation limits model complexity while the RBF kernel still allows for nonlinear relationships. KNN produced the lowest test R^2 among the nonlinear models, suggesting that distance-based averaging was less robust in the small-sample feature spaces. TabPFN showed comparatively stable repeated CV performance, but its weaker E_{v1} prediction indicates that this stability did not translate into balanced multi-output generalization.

For Feature Set 1, SVR achieved the best E_{v2} prediction, with $R^2 = 0.34$ and RMSE = 7.1 MPa. RF achieved the best average test performance, with an average R^2 of 0.14, and also produced the lowest RMSE of 0.34 for the E_{v2}/E_{v1} ratio. For Feature Set 2, TabPFN achieved the highest E_{v2} performance, with $R^2 = 0.45$ and RMSE = 6.5 MPa. RF again achieved the best average test performance, with an average R^2 of 0.22. SVR produced the lowest RMSE for the E_{v2}/E_{v1} ratio, at 0.34, while RF followed closely at 0.35. These results indicate that the preferred model depends on the

criterion used. TabPFN is appealing for practical QA since E_{v2} is the primary design-relevant target. Meanwhile, RF or SVR may be better suited for balanced multi-output prediction or for E_{v2}/E_{v1} estimation.

The poorer test performance on E_{v1} indicates that it is less reliably inferred from roller response alone, partly because the first loading cycle is sensitive to surface unevenness. In addition, the deformation moduli used as target values should not be treated as absolute ground truth, as they inherit uncertainties from the PLT procedure. These uncertainties mainly arise from the localized nature of the test, spatial variability within the compacted layer, and the contact condition between the loading plate and the ground.

The low and sometimes negative R^2 values should be interpreted in light of the test set's limited size, where a small number of individual prediction errors can strongly affect the calculated statistics. With larger and more diverse datasets, both predictive accuracy and the stability of the feature-contribution interpretations presented in Section 4.4 are expected to improve. The models developed in this study should therefore be regarded as decision-support tools that complement, rather than replace, conventional spot tests in QA workflows.

Table 1. Model performance summary.

Set	Model	Train R^2 E_{v1}	Train R^2 E_{v2}	Test R^2 E_{v1}	Test R^2 E_{v2}	Test RMSE E_{v1} (MPa)	Test RMSE E_{v2} (MPa)	E_{v2}/E_{v1} RMSE	CV R^2 avg ± std
1	MLR	0.70	0.72	-0.71	-0.01	5.7	8.8	0.36	0.52 ± 0.22
	RF	0.71	0.75	-0.02	0.29	4.4	7.4	0.34	0.43 ± 0.27
	XGBoost	0.72	0.76	-0.12	0.15	4.6	8.1	0.36	0.42 ± 0.30
	SVR	0.70	0.66	-0.28	0.34	4.9	7.1	0.35	0.48 ± 0.23
	KNN	0.67	0.71	-0.55	0.13	5.4	8.2	0.38	0.42 ± 0.30
	TabPFN	0.86	0.83	-0.91	0.28	6.0	7.5	0.41	0.54 ± 0.24
2	MLR	0.73	0.76	-0.73	0.29	5.7	7.4	0.38	0.47 ± 0.27
	RF	0.72	0.75	0.10	0.34	4.1	7.1	0.35	0.38 ± 0.30
	XGBoost	0.71	0.75	0.03	0.28	4.3	7.5	0.37	0.34 ± 0.27
	SVR	0.67	0.67	0.04	0.32	4.3	7.2	0.34	0.39 ± 0.21
	KNN	0.62	0.68	-0.34	0.29	5.0	7.4	0.38	0.40 ± 0.29
	TabPFN	0.85	0.86	-0.97	0.45	6.1	6.5	0.43	0.51 ± 0.26

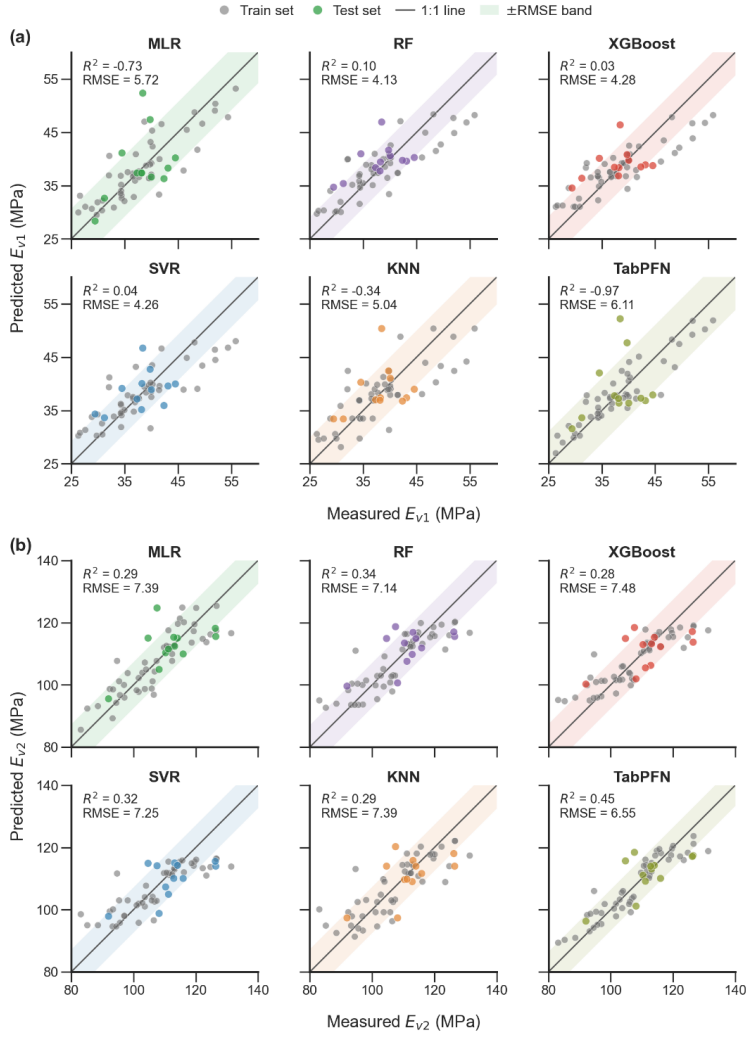


Fig. 3. Actual versus predicted values of (a) E_{v1} and (b) E_{v2} across models for Feature Set 2.

4.2 Response Characteristics over ICMVs

The dumbbell plot shown in **Fig. 4** compares the test performance of the best models across feature sets. For each target variable, the model with the highest R^2 on the test set is selected. The connecting lines indicate the performance difference between Feature Sets 1 and 2. The results show that performance on E_{v1} and E_{v2} is consistently better with Feature Set 2 than with Feature Set 1. This suggests that preserving relatively raw and complete response characteristics helps the algorithms better map to soil stiffness. The ICMVs selected in Feature Set 1 show weaker predictive capability, likely due to their high intercorrelation, as shown in **Fig. 1**.

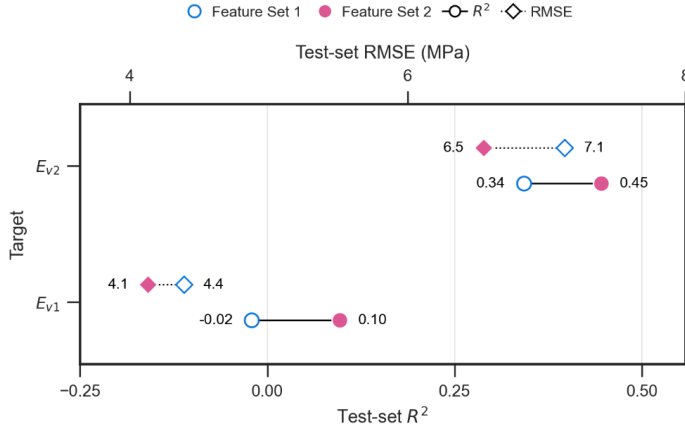


Fig. 4. Target-wise best test performance for the two feature sets.

4.3 Feature Importance

Based on mean absolute SHAP values computed over all 60 samples, the feature importance rankings for E_{v2} prediction using Feature Set 2 are summarized in **Table 2**. Across the nonlinear models, the second-harmonic acceleration amplitude A_2 was the most consistently top-ranked feature, and k_1 , k_2 , and z_d also ranked among the most influential.

The beeswarm plot in **Fig. 5** further illustrates how individual feature values contribute to TabPFN predictions. Features are ranked from top to bottom by global importance, calculated as the mean absolute SHAP value. Points are colored by the feature's actual value, with red and blue indicating high and low values, respectively. The horizontal SHAP value indicates the contribution relative to the baseline. Positive contributions tend to increase the model prediction, while negative contributions tend to decrease it. Note that feature effects should be interpreted as model associations rather than causal mechanisms.

The features A_2 , k_1 , z_d , and $v_{\max}$ showed wide ranges of contributions. Higher values of A_2 , k_1 , z_d , k_2 , and $E_{\text{unloading}}$ generally contributed positively to the prediction, whereas higher values of $v_{\max}$, E_{loading} , and A_1 contributed negatively. This pattern is physically reasonable, as stronger harmonic acceleration components, higher stiffness, larger vibration amplitudes, and greater energy return to the drum are typically expected when compacting stiffer ground. The two distinct clusters observed for $v_{\max}$ and E_{loading} likely reflect the different compaction capabilities of the two rollers. Larger A_1 values may correspond to response regimes in which an increased fundamental component is linked to a lower predicted E_{v2} , after the effects of high-ranking features such as A_2 have been accounted for. A comparison of the rankings of k_1 and E_{loading} with those of k_2 and $E_{\text{unloading}}$ further indicates that the loading branch provides more informative features for E_{v2} prediction than the unloading branch. However, the unloading stiffness k_2 remains important in several models.

Table 2. Feature importance ranking for E_{v2} prediction across the nonlinear models.

Rank	RF	XGBoost	SVR	KNN	TabPFN
1	A_2	A_2	A_2	A_2	A_2
2	E_{loading}	k_2	k_1	k_1	k_1
3	k_2	z_d	z_d	k_2	z_d
4	k_1	k_1	k_2	z_d	$v_{\max}$
5	z_d	$E_{\text{unloading}}$	A_1	A_1	E_{loading}
6	$E_{\text{unloading}}$	E_{loading}	$E_{\text{unloading}}$	$E_{\text{unloading}}$	k_2
7	$v_{\max}$	A_1	E_{loading}	E_{loading}	$E_{\text{unloading}}$
8	A_1	$v_{\max}$	$v_{\max}$	$v_{\max}$	A_1

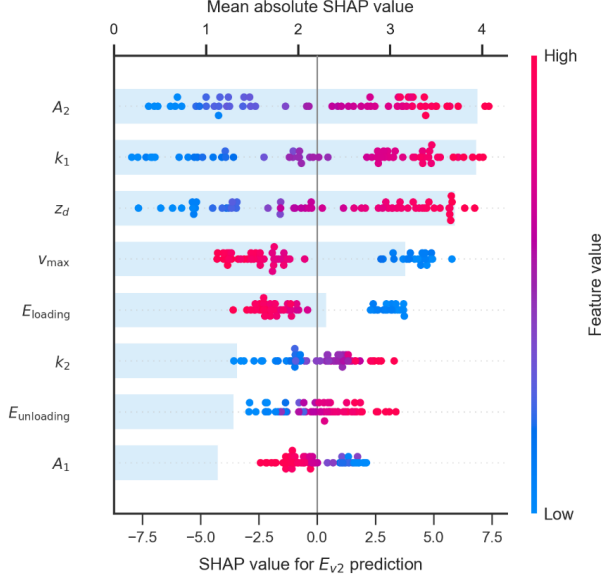


Fig. 5. SHAP summary plot for E_{v2} prediction with TabPFN.

5 Conclusions

This study developed a machine-learning framework to estimate deformation moduli from compaction measurements, using a dataset obtained from full-scale laboratory tests. The main findings are summarized below.

- Curated response characteristics improved E_{v2} prediction. The best result on Feature Set 2, achieved by TabPFN, reached $R^2 = 0.45$ and $\text{RMSE} = 6.5$ MPa, compared with the best result of $R^2 = 0.34$ and $\text{RMSE} = 7.1$ MPa from SVR on Feature Set 1.
- TabPFN performed well for the primary E_{v2} target on the small dataset and required no hyperparameter tuning. However, it was not the best model for all criteria. Generally, RF achieved the best average multi-output performance and had the lowest RMSE for the E_{v2}/E_{v1} ratio.
- Prediction of E_{v1} remains challenging. Several models showed weak or negative test performance, indicating that E_{v1} is less reliably inferred from roller response alone. This limitation is likely related not only to the small sample size but also to the inherent uncertainty of E_{v1} in the PLT.

- SHAP analysis identified second-harmonic acceleration amplitude, loading and unloading stiffness, and displacement amplitude as influential predictors of E_{v2} , providing physical grounding for the data-driven models.
- The simultaneous prediction of E_{v1} and E_{v2} enabled estimation of the E_{v2}/E_{v1} ratio, with the lowest RMSE of 0.34 achieved by SVR on Feature Set 2. This provides a data-driven proxy for residual compaction potential, though its accuracy is limited by uncertainty in the E_{v1} prediction.

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