# Virtual Construction Equipment Sensor for Determining Soil Stiffness during Compaction

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**Abstract – Processes on construction sites are characterized by a high proportion of manual work, rapid variability and harsh working conditions. As a result, the level of digitalization and automation as well as productivity is low. In the near future, digital assistance and documentation systems will be used to counteract these shortcomings. To achieve this, machines must be able to learn more about their work processes and pass this information on to information systems. Innovative sensor systems for recording machine performance are in demand. Digital (BIM) models of the objects to be built offer the possibility of providing target quality data for machine operation and storing the achieved quality data after construction.**

**In soil compaction using vibratory plates, soil stiffness is still recorded manually today, although automated recording would be conceivable. Relevant input and output variables for the compaction process are to be collected for the soil compaction application. On this basis, a sensor system for determining soil stiffness during compaction is designed and built as a prototype. This will result in a multivariable system with influencing, measured and target variables (virtual sensor), which can be used for the structured development of statistically meaningful test series to determine the correlation between measured values and the quality of the compaction process (soil stiffness). Robust algorithms for recording and transferring the degree of soil compaction during compaction were derived from the tests on the chair's own test site and demonstrate that measuring the absolute soil stiffness during compaction with vibratory plates is possible. This conclusion provides the basis for increased quality, automation and digital continuity of future earthworks.**

**Keywords –**
**Virtual Sensor; Compaction; Soil Stiffness; Automation**

## 1 Introduction

Compaction is a quality-defining subprocess of earthworks. As other construction processes today, it involves multiple manual workflows and is rarely digitized. An excavator prepares the earth surface specified in building plans and the specifications that has to be compacted according to norms. Subsequently, the compactor has to be placed in the area that should be compacted. The area is compacted and after completion the resulting ground stiffness is measured. Depending on the measurements the compaction is continued or the measurement receipts are documented in the construction diary and the compactor is removed from the area. The following construction processes rely on the documented data e. g. in building on the created surface. Figure 1 visualizes the compaction process of today.

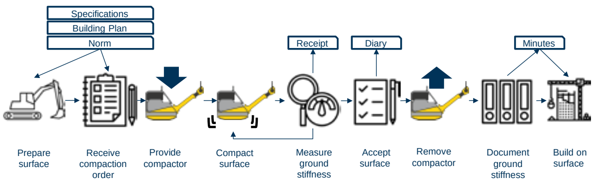


Figure 1: Current compaction process in earthwork construction

On top of the high degree of manual work in this process and the incontinuity of the information flow along the process, there is potential to fusion the process steps “receive compaction order”, “compact surface”, “measure ground stiffness”, “accept surface”, and “document ground stiffness”, by developing a compaction quality control system. This system should receive the target ground stiffnesses from a BIM-model, measure the ground stiffness during compaction, and document the as-built ground stiffnesses in the BIM-model. Therefore, the research question of this paper is “How can a virtual construction equipment sensor reliably determine the soil stiffness during compaction in earthwork construction?".

In order to answer the research question, this paper will present the State of Science and Technology (2) on the compaction process, compaction progress determination and technical functionality of equipment-integrated methods. The state of the art is subsequently extended through the description of the development of a virtual sensor (3). The developed virtual sensor is validated in compaction test series (4). Finally, the paper closes with a discussion, conclusion and outlook.

# 2 State of Science and Technology

## 2.1 Compaction Process

According to Richter and Heindel [1] soil compaction is a process, reducing the material's porosity while simultaneously enhancing its load capacity. Thereby, many different parameters influence the compaction process. The most significant being the soil type and grain size distribution, as well as the water content inside the material and the compaction equipment used [2–4].

The compaction effect produced by vibratory plates is based on the short repeal of friction between individual grain particles because of the vibrations. This leads to a rearrangement of the material bulk into a tighter packed substrate [1, 4]. To generate the vibrations on such equipment, one or more excitation shafts with an eccentric mass are coupled to an engine and transfer them into the ground via the base plate. If two or more shafts are used, changing their respective phase angle to one another results in a change of working direction, because of a different resulting force vector. Therefore the worker can easily manipulate the driving direction of the compactor [2, 5, 6].

## 2.2 Compaction Progress Determination

Measuring the achieved soil stiffness after the compaction with vibratory plates is mostly done by hand after the job is completed. Therefore, if an insufficient ground stiffness value is detected, the affected area has to be reworked. The used ground stiffness measuring methods often require special equipment and trained workers to ensure an accurate result. Among the most used control methods are the Proctor-test according to DIN 18127 [7], the static plate load test (DIN 18134) [8], the dynamic plate load test with the light weight deflectometer [9] as well as various different field tests based on replacement procedures and cut out soil samples in DIN 18125-2 [10]. Furthermore, radioactive radiation deflection methods [2, 3] and the measurement of seismic waves according to [2] and [4] can be considered a valid option to determining the compaction state. The absolute compaction value of the underlying surface can be evaluated using such methods.

The exception to the rule is made by an effort done by the different manufacturers of vibratory plates to incorporate soil stiffness measurement systems on their equipment [11–15]. These systems are derived from well-established continuous compaction control systems used on roller compactors [1, 16, 17].

However, due to the nondeterministic vibration behaviour of compaction plates [11] and the cyclic loss of ground contact, the methods on vibratory plates lack the precision and reliability of their roller compactor counterparts. Furthermore, in contrast to the previously described conventional systems, with machine-based approaches it is only possible to detect the soil stiffness increase from one pass to another. The measured compaction states are therefore called relative compaction values.

Because these systems provide the base of research in this paper, the next part of the state of technology is dedicated to the basic functionality of soil stiffness measurement systems on vibratory plates.

## 2.3 Technical Functionality of Equipment-integrated Methods

The patents described in [11–14] are all based on the collection and analyzation of vibrations on various different parts of the equipment. For example, the relative movement of the upper mass to the lower mass. The measured accelerations are then further processed by different filters and mathematical methods to ensure a stable output value. However, the detailed execution of the system complexity and sensor architecture varies vastly between the different manufacturers. The Bomag system [13] is able to predict the relative compaction increase quite simply by calculating the quotient of two characteristic parts of the observed vibration. On the other hand, looking at the approach from Wacker Neuson [14] with their Compatec system, a compaction value is calculated from solution of the three dimensional differential equations of motion. For those, the expected contact force vector between the ground plate and the soil has to be predicted based on the contact area and the rotation of the base plate. Furthermore, the contact area relies on an estimation itself.

These highly complicated calculation algorithm and the complex construction circumstances led to an impractical result due to too many uncertainties. According to further research, the compatec system is not used on any currently available vibratory plates from Wacker Neuson, but only in a much simpler version. An other approach by Weber [12] matches the current machine vibrations with the taught in values in an internal database. To ensure an accurate relationship between the measured and reference values, the exact correlation for each construction project has to be determined by a calibration test ahead of the compaction work.

In conclusion, none of the above-described systems are able to determine an absolute compaction value which can be used to validate the executed work for every part of the compacted area.

# 3 Virtual Sensor Development

This chapter explains the development process of the virtual sensor hardware and the corresponding software. In addition, the setup of a first test environment, allowing for simultaneous testing and development of the sensor, including the experimental procedure are discussed. At the end, the gathered data is processed and analyzed, to derive a compaction value based on the ground stiffness from the measured sensor data.

## 3.1 Hardware

To determine a suitable hardware setup for measuring parameters correlating with the soil stiffness, a compaction influence parameter overview was established. Afterwards, fitting sensor solutions measuring the individual aspects are researched and structured in a morphological box (see Figure 2). Other variables such as mounting position, additional user input and possible correlation partners are added.

| Features | | Solution approaches | | | | | |
|---|---|---|---|---|---|---|---|
| 1st order features | 2nd order features | 1 | 2 | 3 | 4 | 5 | 6 |
| Sensor position | Sensor position | Upper mass | Lower mass | Upper and lower mass | Base plate | | |
| | Physical measure | Vibrations | Water content | Soil density/ pore fraction | Body/ airborne sound | Grain sizes | Grain size distribution |
| | Sensor principle | Acceleration sensor | Ultrasonic sensor | Resistance measurement | Acoustic sensors | Moisture meter | Capacitance measurement |
| Data management | Data acquisition | Continuous | Discrete measuring points | Measurement runs | Calibration drives | | |
| | Operator input | None | Soil type | Calibration data (table) | Desired degree of compaction Calibration | Calibration measurement | Data acquisition with soil probe |
| | Possible correlation | Degree of compaction | Static soil stiffness | Dynamic soil stiffness | FDVK value | Proctor density | Compaction performance |

Figure 2: Morphological box

A multicriterial evaluation compares the different possibilities regarding their cost, technical feasibility, and suitability for implementation in series production machines. On top, sensors for measuring moisture and the grain sizes of the material were adapted from similar use cases and bench tested in individual experiments.

In the end, two different sensor setups were derived from the morphological box. One uses inertia measurement units (imus) to gather vibration information of the upper and lower mass simultaneously. The other one measures the acoustic emissions of the plate during compaction with a highly sensitive microphone. For sensor communication and power supply, a microcomputer in form of a raspberry pi 4 is utilized. This also acts as a communication interface with an external computer via a Wi-Fi-hotspot and VNC-server.

The mounting position of all sensors is in the middle of the backside of the machine to ensure short wires and a minimal influence of the exhaust system on the recorded sound data (see Figure 3).

Figure 3: Sensor placement on the vibratory plate

## 3.2 Software

The software package contemplating the physical sensors is composed of different parts for every application. As the imu’s are coupled to the raspberry pi via a separate microcontroller based on an esp32-pico chipset, the work from Tanaka [18] is adopted to fit the needs of this research. In addition, the audio software ‘audacity’ is installed on the raspberry pi for capturing the noise emissions.

For recording the acceleration data transmitted via USB from the sensor’s microcontroller, the raspberry pi uses the terminal emulator ‘Putty’. This enables the storage of the six individual acceleration data in an excel-file.

## 3.3 Test Site Setup

Besides the hard- and software setup, at suitable test area is required for doing the data collection test runs. The test site consists of a temporary compaction field made up of mixed-particle sized gravel, located on the concrete floored outdoor test area of the chair. The compaction area is constrained on one side by large concrete blocks and sloped on the other. This ensures an easy loosening up of the compacted material with a wheel loader. For faster material handling times, the test setups are made up alternating both sides of the middle separation layer. The material height for the different test fields varies from 30 to 50 cm depending on the desired experiment goal.

In addition, ten marks spacing one meter each are placed on the concrete blocks to help guide the exact measuring position of the conventional compaction determination method as a reference. Therefore, a dynamic plate load test with the light weight deflectometer model ZFG 2000 by ZORN with 300 mm base plate diameter and a 10 kg drop weight is used, because its widely spread application on real world construction sites and its ease of use.

Figure 4 shows a sketch of the utilized test site setup and the position of the reference marks (MP).

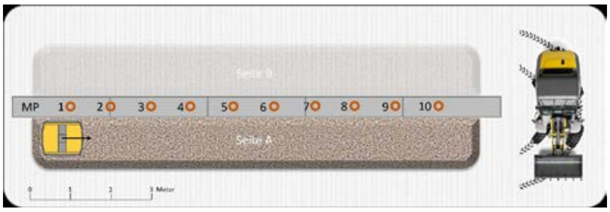


Figure 4: Test site setup, machine sketches from [19] and [20]

For all the test runs in the initial batch of experiments, a heavy remotely controlled compaction plate of type Wacker Neuson DPU110rLec970 [21] with a maximum centrifugal force of 110 kN, an operating weight of around 810 kg and a base plate width of 970 mm was used. After placing the equipment at the end of the test field, back and forth passes are carried out. In between each alternation, the achieved ground stiffness values are measured at the reference points inside the lane.

### 3.4 Data Collection

The experiments took place in cold but mostly dry weather. In total, eight different test fields were created with a cumulated amount of 30 passes with the vibratory plate. Table 1 gives an overview of the individual setups for each experiment.

Table 1: Test fields and their setups

| Name | Number of passes | Material height | Direction of first pass |
|---|---|---|---|
| Field 0 | 4 | 50 cm | Forwards |
| Field 1 | 6 | 50 cm | Backwards |
| Field 2 | 5 | 50 cm | Forwards |
| Field 3 | 4 | 50 cm | Backwards |
| Field 4 | 4 | 30 cm | Forwards |
| Field 5 | 2 | 30 cm | Backwards |
| Field 6 | 2 | 30 cm | Forwards |
| Field 7 | 3 | 30 cm | Backwards |

### 3.5 Evaluation Algorithms

The first step of analyzing the measured data is creating a reference value curve for the dynamic ground stiffness from the light weight deflectometer. The individual data points can be connected to form a continuous line, as it is not expected, that the soil stiffness jumps rapidly. Furthermore, outliers due to measurement errors have to be considered when evaluating the sensor data in comparison to the references.

To get a feel for the gathered sensor data, the acceleration values and the audio recording are first plotted in their time representation. From those depictions it is possible to determine the different work modes of the equipment, such as idle, engine run-up and compaction operation. The plot also reveals the overflow of the imu on the lower mass due to an insufficient measuring interval of the imus.

For further analysis, Kuttner and Rohnen [22] differentiate between methods in the time domain and methods in the frequency domain. The Fourier analysis is a prominent representative of a frequency domain method for analyzing dominant vibration parts and their harmonics. For best results, it is recommended to prefilter the signal with a lowpass filter whose parameters are set with the Nyquist-Shannon-Theorem in mind [22]. According to Werner [23], the resolution of the resulting frequency spectrum when looking at a time discrete signal can be improved by using zero-padding.

Other closer looked at methods include different envelope techniques, such as described by Kuttner and Rohnen [22], but also statistical procedures. In this case the focus lies on the distribution of the amplitude density depicted as an histogram [24] and counting methods based on the rainflow-principle [25].

In addition, Takami et. al. [26] as well as Kanokogi and Takami's [27] approach of matching sensor data into a given group or to a reference value via neural network machine learning were also explored. It is remarked by the authors, that due to Wolpert and Macready's [28] no-free-lunch-theorem, every machine learning network has to be adopted to the specific problem, otherwise the full potential cannot be exploited.

Most of the before mention methods applied to the measured sensor data, does not lead to any visible differences when looking at data from low and high ground stiffness. However, by examining the Fourier spectrum of the acceleration values, there is a significance in the vertical vibration of the upper mass in the low frequency area. Upon closer inspection, the dominant frequency may well be the eigenfrequency of the upper mass, when compared to the experiments and simulations from Lohr [29]. Furthermore, the frequency and amplitude of this deep vibration changes with the soil stiffness the plate is driven over and therefore is also visible in the audio data. For this main finding in the first set of experiments, the further evaluation of the correspondence shall be explained in more detail.

The sensor data is lowpass filtered at first and then divided into sections of equal time length. Each section is analysed with a fast Fourier transform (fft) algorithm [22, 23] and the peaks and frequency of the dominant low end are extracted. Due to no direct analytical correlation between these peaks and the soil stiffness, a genetic algorithm (ga) is set up to optimize the data processing and the parameters of an analytic correlation function.

The ga is an evolutionary algorithm inspired by natural selection and survival of the fittest. It was developed by Goldberg in the 1980s and is widely used for such optimization problems [30].

When used on the data of one test field, the achievable correlation values are quite decent for the best parameter sets. Transferring the same algorithm to a yet unknown data set does unfortunately not provide the same performance. There were different promising parameter sets tested on all the available data, but the resulting values did not converge.

In summary, the first tests failed to meet the requirements in terms of a compaction value correlated from the sensor data. However, a lot of lessons were learnt about the test environment, as well as the sensor data and its analyzation methods. For example, the methods from Takami et. al [26] as well as their predecessors Kanokogi and Takami [27] seem to be a promising pre-processing for the measurement data. Overall, machine learning algorithms are most promising to classify the pre-processed data.

This knowledge is put to use when enhancing the test setup and sensor system for a follow-up experiment.

# 4 Verification & Validation

In this chapter, the changes to the test setup based on the gathered experience from the previous research is presented. Also, the second round of data collection and its analysis is discussed.

## 4.1 Improved test setup

The first major change for the second round of data collection is the switch to a smaller vibratory plate for higher resolution in the individual compaction passes. From now on, a preproduction sample from Wacker Neusons new DPU6560 range with a maximum centrifugal force of 65 kN, an operating weight of 475 kg and a base plate width of 600 mm is utilized. In addition, the overflowing imu-sensor on the lower mass is upgraded to a much more capable unit.

As the operating system on the raspberry pi is switched to ROS2, it now supports an interface to an existing GNSS position measuring system via real-time kinematics positioning. Through this add-on it is possible to exactly track the machine’s position and correlate it with the measured sensor data and the reference values from the plate load test.

On the test site side, the total length of the area is enlarged to ensure adequate areas for the start and stop of the compaction plate. Therefore, the impact of the startup and stop processes on the measured parameters can minimized.

## 4.2 Data collection

As the evaluation of the first data set showed, that it is fortunate to have a large number of passes on each test field, the test procedure is slightly adopted. Instead of doing only 2 or 3 passes on a field with 30 cm of material, the bulk height is kept constant at 50 cm throughout the whole test. In combination with the lower compaction power of the smaller plate, more passes per field can be executed. Table 2 shows the chosen parameter sets for each individual test field. It should be highlighted, that the passes on field 4 and field 5 are all carried out in the same direction to eliminate one additional variable when analysing the data.

Table 2: Test field setups for the second round of data collection

| Name | Number of passes | Direction of first pass | Compaction strategy |
|---|---|---|---|
| Field 1 | 12 | Forwards | Alternating |
| Field 2 | 11 | Forwards | Alternating |
| Field 3 | 8 | Backwards | Alternating |
| Field 4 | 11 | Forwards | Forwards |
| Field 5 | 7 | Backwards | Backwards |

## 4.3 Data evaluation

For the data analysis from the second set of tests, the methods from Takami et. al [26] as well as their predecessors Kanokogi and Takami [27] mentioned in subsection 3.5 are applied in more detail.

The goal is to discretise the measured soil stiffness values into different classes and matching the corresponding sensor data signal intervals from the imus with the help of machine learning algorithms.

Due to a different compaction behaviour depending on the working direction of the plate, two separate algorithms have to be trained in order to achieve the best possible results. For training, the data sets from field 4 and field 5 are used, as these are obtained while keeping a constant driving direction. In order to prepare the data, the signals are first filtered and then divided into 10 equal length section corresponding to the 10 measuring points for the reference values. Afterwards, each section is transformed into the frequency spectrum using the fft-algorithm.

To classify the data, the dynamic soil stiffness values measured with the light weight deflectometer are grouped into four equal sized intervals spanning the whole measuring range. These classifications in combination with the pre-processed frequency spectra are then input into the algorithms as training data.

In an iterative measure, various different algorithm parameters are obtained, from which the most promising are used for validation of this method on the remaining data sets.

### 4.4 Algorithm validation

In this chapter, the previously derived parameter set for the algorithms are tested on the so far unused data sets from fields 1-3.

The results of this generalization are all quite close together with the best parameter set for the forward working direction having a correct classification rate of a little over 80 %. When looking at the backward working direction, the performance is with close to 70 % a little bit lower. This may be caused by a smaller available data set for training in the beginning and therefore not being able to find an algorithm configuration with the same level of sophistication.

When combining the performance of both algorithms, 76 % of all data generated in the second batch of experiments are classified correctly. Figure 5 shows the confusion matrix of the combined algorithms for data analysis. The diagonal shows all correctly classified data samples and below/on the right the performance of each row/column is summarized in percent.

| | Predicted Class | | | | |
|---|---|---|---|---|---|
| True Class | **23** | 27 | 1 | | 45,1 |
| | | **224** | 43 | 9 | 81,2 |
| | | 29 | **108** | 4 | 76,6 |
| | | 1 | 1 | **10** | 83,3 |
| | 100 | 79,7 | 70,6 | 43,5 | |

Figure 5: Confusion matrix of the combined algorithms

Looking at the confusion matrix, the validation of the developed algorithms can be seen as a success. The falsely classified data is close to the diagonal, which shows, that these samples were placed in the neighbouring class. This may happen due to the real value being close to one of the class borders. From a total of 480 data samples only 11 (2,29 %) are not located close to the diagonal.

## 5 Discussion, Conclusion & Outlook

As the algorithm is able to determine the interval of more than three quarters of all measurement data sets to their actual soil stiffness values, the previously set goal was achieved. The algorithm matches the reliability asked for in the research question “How can a virtual construction equipment sensor reliably determine the soil stiffness during compaction in earthwork construction?”. The algorithms in combination with the sensor hardware (subsection 3.1) forms a virtual sensor, that is able to accurately determine the absolute ground stiffness of compacted soil in our test study.

The findings of this publication are limited in the amount of tests and data that were used. Exemplarily, only one kind of soil was used in the test runs and the sensor was mounted on two different vibratory plates. Until there are no further experiments with other vibratory plates and material, the significance of these findings is limited to the scope of the presented test runs. However, the findings of our research project indicate that measuring ground stiffness during compaction is possible with our current virtual sensor, which will be optimized in forthcoming studies and iterations.

The results of our research have shown that reaching the main goal of reducing the high degree of manual work in the compaction process and creating a continuous information flow along this process is possible. The virtual sensor for compaction quality control forms the basis for combining the process steps “receive compaction order”, “compact surface”, “measure ground stiffness”, “accept surface”, and “document ground stiffness”. The functionality of the envisioned compaction quality control system is depicted in Figure 6.

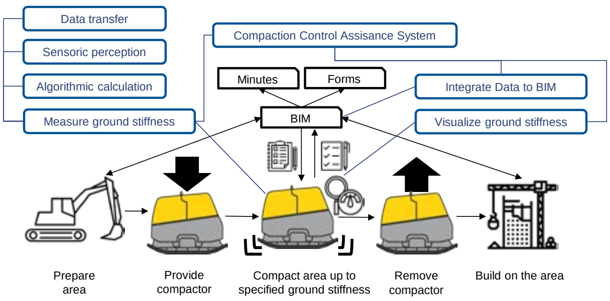


Figure 6: Functionality of the envisioned compaction quality control system

Future research should focus on increasing the classification accuracy of the algorithms and a cost and quality optimization of the hardware in use. Additionally, more tests have to be carried out to determine the performance of the virtual sensor in other equipment and soil combinations. In order to transform the current compaction process into the envisioned system, BIM-model interfaces have to be crated [31] and the value of the solution has to be demonstrated to practitioners in order for the system to be accepted by them.

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## References

[1] D. Richter and M. Heindel, *Straßen- und Tiefbau*. Vieweg+Teubner, 2011.

[2] W. Striegler and D. Werner, *Erdstoffverdichtung*, 2nd ed. Berlin: VEB Verlag für Bauwesen, 1976.

[3] R. Voss and R. Floss, *Die Bodenverdichtung im Straßenbau*, 5th ed. Düsseldorf: Werner-Verlag, 1968.

[4] W. Dachroth, *Handbuch der Baugeologie und Geotechnik*, 4th ed. Berlin, Heidelberg: Springer Berlin Heidelberg, 2017.

[5] Ammann Group. “Produktkatalog - APH Rüttelplatten: APH Serie Hydrostatische Rüttelplatten.” https://www.avesco.ch/fileadmin/avescoproducts/c3c0b8e4f1fc59d5d62df7cf4f8efcad.pdf (accessed Nov. 23, 2022).

[6] Wacker Neuson SE, 80809 München, DE. “Broschüre Vibrationsplatten.” https://www.wackerneuson.de/media/contentserv/71960.pdf (accessed Jan. 11, 2023).

[7] *Baugrund, Untersuchung von Bodenproben - Proctorversuch*, DIN-18127, DIN Deutsches Institut für Normung e.V., Berlin, Sep. 2012.

[8] *Baugrund - Versuche und Versuchsgeräte - Plattendruckversuch*, DIN-18134, DIN Deutsches Institut für Normung e.V., Berlin, Apr. 2012.

[9] Forschungsgesellschaft für Straßen- und Verkehrswesen (FGSV), *Technische Prüfvorschriften für Boden und Fels im Straßenbau - Teil B 8.3: Dynamischer Plattendruckversuch mit dem Leichtem Fallgewichtsgerät: TP BF-StB Teil B 8.3*, 2012nd ed. (FGSV R1 - Regelwerke). Köln: FGSV Verlag GmbH, 2012.

[10] *Baugrund, Untersuchung von Bodenproben – Bestimmung der Dichte des Bodens – Teil 2: Feldversuche*, DIN-18125-2, DIN Deutsches Institut für Normung e.V., Berlin, Nov. 2020.

[11] R. Anderegg, U. Drees, A. Kuban, and D. Von Felten, “Verfahren zur Ermittlung einer Bodensteifigkeit und Bodenverdichtungsvorrichtung,” EP 1 516 961 B1.

[12] W. Latt and A. Kurzweg, “Verfahren und Vorrichtung zum Messen von Bodenparametern mittels Verdichtungsmaschinen,” DE 10 2010 060 843 B4.

[13] N. Laugwitz, “Verfahren und Vorrichtung zur Bestimmung des Verdichtungsgrades bei der Bodenverdichtung,” DE 10028949 A1.

[14] Wacker Neuson SE, 80809 München, DE, “Verfahren und Vorrichtung zum Messen von Bodenparametern mittels Verdichtungsmaschinen,” DE 10 2006 008 266 B4.

[15] M. Steffen, “Bodenverdichtungsvorrichtung zum Verdichten eines Bodenbereichs,” DE 10 2019 107 219 A1.

[16] J. Pistrol, F. Kopf, and W. Völkel, “Verfahren zur Ermittlung des Verdichtungszustandes eines Untergrunds,” EP 3 176 324 B1.

[17] P. Corcoran and L. Chi, “Device and process to measure ground stiffness from compactors,” WO 2015/112412 A1.

[18] M. Tanaka. “I2C MPU6886 IMU Library.” https://github.com/tanakamasayuki/I2C_MPU6886 (accessed Apr. 14, 2023).

[19] Kramer Werke GmbH, 88630 Pfullendorf, DE. “EINSTEIGEN UND LOSFAHREN Die Rad- und Teleskopradlader 5035/5040/5050/5055/5065/5065T.” https://www.kramer-online.com/media/contentserv/37131.pdf (accessed Apr. 16, 2023).

[20] Wacker Neuson SE, 80809 München, DE. “Broschüre Verdichtung.” https://www.wackerneuson.de/media/contentserv/108754.pdf (accessed Apr. 16, 2023).

[21] Wacker Neuson SE, 80809 München, DE. “Produktinformationsblatt DPU110rLec970.” https://www.wackerneuson.de/media/contentserv/64139.pdf (accessed Apr. 23, 2023).

[22] T. Kuttner and A. Rohnen, *Praxis der Schwingungsmessung*. Wiesbaden: Springer Fachmedien Wiesbaden, 2019.

[23] M. Werner, *Digitale Signalverarbeitung mit MATLAB®*. Wiesbaden: Springer Fachmedien Wiesbaden, 2019.

[24] J. S. Bendat and A. G. Piersol, *Random data: Analysis and measurement procedures* (Wiley series in probability and statistics). Hoboken, N.J: Wiley, 2010. [Online]. Available: https://onlinelibrary.wiley.com/doi/book/10.1002/9781118032428

[25] Y.-L. Lee and T. Tjhung, "Rainflow Cycle Counting Techniques," in *Metal Fatigue Analysis Handbook*, Y.-L. Lee, M. E. Barkey, and H.-T. Kang, Eds., Elsevier, 2012, pp. 89–114.
[26] G. Takami, M. Tokuoka, H. Goto, and Y. Nozaka, "Machine Learning Applied to Sensor Data Analysis," in *Yokogawa Technical Report English Edition Vol. 59 No. 1*, Yokogawa Corporation, Ed., 2016, pp. 27–30.
[27] H. Kanokogi and G. Takami, "Machine Learning Applied to Sensor Data Analysis: Part 2," in *Yokogawa Technical Report English Edition Vol. 60 No. 1*, Yokogawa Corporation, Ed., 2017, pp. 35–38.
[28] D. H. Wolpert and W. G. Macready, "No free lunch theorems for optimization,", *IEEE Trans. Evol. Computat.*, vol. 1, no. 1, pp. 67–82, 1997, doi: 10.1109/4235.585893.
[29] W. Lohr, *Untersuchungen zum Schwingungsverhalten von Vibrationsplatten mit Hilfe der Mehrkörperdynamik* (Zugl.: Siegen, Univ., Diss., 2004) (Berichte aus dem Maschinenbau). Aachen: Shaker, 2005.
[30] D. E. Goldberg, *Genetic algorithms in search, optimization, and machine learning*, 30th ed. Boston: Addison-Wesley, 1989.
[31] M. Schöberl, S. Offinger, T. Goldfuß, S. Kessler, J. Fottner, “BIM-integration of light construction equipment” in *Proceedings of the 39th international symposium on automation and robotics in construction (ISARC 2022)*, Bogota, Colombia, International Association for Automation and Robotics in Construction (IAARC), 2022, https://doi.org/10.22260/ISARC2022/0027.