Application of hybrid machine learning based quality control in daily site management

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ABSTRACT: This paper presents a system that combines KPI with autoencoders to implement a hybrid machine learning system. The goal here is to investigate workflows which permit the site manager to use the hybrid machine learning systems as a decision support tool. The workflows are explained by means of case studies, demonstrating the application of the hybrid system to detect both element as well as site related quality issues. In addition to that, the detection of anomalies regarding execution efficiency assist the project manager to optimize the sequence of work on site.

Keywords: ground improvement, quality control, machine learning, key performance indicators.

1 INTRODUCTION

The evaluation and analysis of machine data to support project managers in their daily business was introduced by Keller more than 10 years ago (Zöhrer & Wondre, 2012). Improving of the quality assurance procedures was a focus right from the start. Falk et al. 2011 describe the development and challenges of machine data acquisition and the geotechnical interpretation of this data. Key performance indicators (KPI) were introduced with goal of characterizing soil and execution parameters; these can be calculated directly from the machine data. The tool named "VibroScan" was the result of this work and it was made available to all of Keller's project managers and their clients.

The concept of a digital twin for vibro-ground improvement was later introduced, (Khalili-Motlagh-Kasmaei et al. 2022), to improve quality control. Then hybrid machine learning was added, i.e., a combination of classical analysis and machine learning (ML), see Terbuch et al., 2022b. The hybrid system computes a set of (KPI) for each element, based on the corresponding multivariate time series data (MVTS), i.e., the real-time machine data. The KPI capture the current status of expert knowledge relating machine data to process properties. The KPI are categorized into groups corresponding to different aspects of the process being executed. The unsupervised machine learning (U-ML) creates a data-model (MLDM) which corresponds to a generalization of the process and influences of a specific site. The MLDM is then used to identify MVTS which are uncharacteristic for the process and/or site. This infers the possibility that the corresponding point is anomalous.

2 HYBRID LEARNING

The hybrid architecture presented here is a refinement of previous work (Khalili-Motlagh-Kasmaei et al. 2022, Terbuch et al., 2022a, Terbuch et al., 2022b, Terbuch et al., 2023). The focus was mainly on variational autoencoders (VAE), (Kingma and Welling, 2013); however, literature suggests that more complex architectures do not necessary lead to better accuracy (Makridakis et al., 2020). Consequently, simpler autoencoders (AE), (Hinton et al. 1986) are also considered here. Due to the limited space for this paper, only the architecture with the best performance is presented. The metrics for comparison of the architectures can be found in Terbuch et al., 2023.

The goal of anomaly detection is to identify patterns in data which are not observed in normal operations (Mavikumbure et al., 2022). Hybrid machine learning combines functionalities and advantages of multiple techniques into one architecture (Makridakis et al., 2020). Here a combination of KPI and an unsupervised machine learning approach, based on autoencoders, has been selected. The combination of two independent and concomitant techniques adds a layer of redundancy to the system. This reduces the risk of overseeing an anomaly.

The KPI capture the expert knowledge relating properties of the produced element to characteristics that can be calculated directly from the machine data. The statistics of each KPI can be used to identify outliers; subsuming the outliers for each point yields a measure of the *outlierness*; for convenience, this value is normalized, see Terbuch et al., 2023 for more details. An autoencoder architecture, implementing unsupervised machine learning, has been selected here to combine with the KPI. The encoders and decoders include recurrent networks; whereby, unidirectional Long-Short term memory (LSTM), (Hochreiter & Schmidhuber 1997) and bi-directional LSTM (BiLSTM), (Graves and Fernandez 2005) layers were considered.

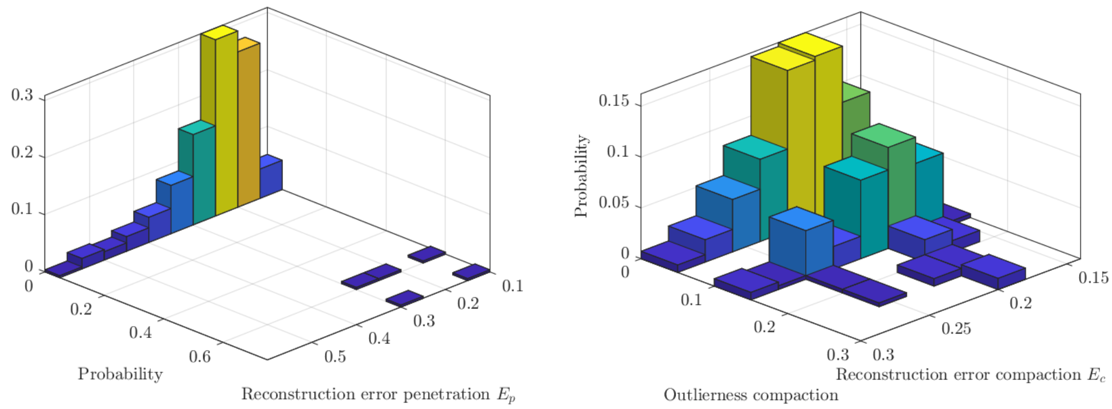

Figure 1. Normalized histogram of the reconstruction error and the outlierness. The ML results were generated using the winning architecture - a VAE-LSTM for the penetration phase on the left and a VAE-BiLSTM for the compaction phase on the right.

Each MVTS is characterized by a set of lower dimensional latent variables computed by the encoder. The decoder reconstructs an approximation for the MVTS from the latent variables (Baldi, 2012). The norm of the difference between the original MVTS and its approximation, is called the reconstruction error. The training phase of the ML aims to minimize this reconstruction error so as to identify an abstraction for the process as a whole. The MVTS used for training are selected using the results of the KPI anomaly detection, therefore it is called KPI-supervised training (Terbuch et al., 2023). In this manner the network learns to reconstruct the data corresponding to normal operation. Conversely, it will produce a higher reconstruction error for non-normal data patterns (Audibert et al., 2022, Garg et al., 2021). This approach is truly unsupervised, since the selection of training samples is done fully automatically without any need of manually labelling data.

The vibro-ground improvement consists of two sub-processes: penetration and compaction. The MVTS are segmented correspondingly. This enables separate, sub-process specific analysis; it also ensures the correct temporal and spatial localization of the source of the anomaly. Different ML architectures (Goodfellow et al., 2016) may be beneficial for the different sub-process. A focus was placed on physics informed (Raissi et al., 2019) hybrid learning. For this reason, the signals: *vibrator amperage, depth* and *pull-down force* were selected, since they permit the computation of *work* (in a physical sense) as a function of time and depth.

The hyperparameters for each architecture were optimized (Terbuch, 2021). Training a network multiple times often leads to differing performance; this is due to the random initialization of the network parameters. Consequently, each architecture was trained 125 times and the stability of the performance was also considered as a criterion for selection. The performance comparison suggested that: the penetration process was best modelled using a BiLSTM-VAE; whereas, optimal performance was achieved for the compaction process with an LSTM-VAE.

3 APPLICATION OF THE IMPROVED QUALITY ASSURANCE PROCEDURE

During a manual comparison of hundreds of installation reports, the project manager can easily loose the overview, especially if complex coherences need to be interpreted. Supported by the hybrid learning system of the Digital Twin such tasks can be improved significantly.

Typically, the first points on a site are used to create an overview of expected site properties and machine behaviour. The corresponding MVTS can now be used to initialize the hybrid system, establishing the MLDM and limit values for the KPI. Consequently, there are no changes required to the current working procedures; nevertheless, the improvement of the level of quality control is achieved. Furthermore, given the geo-referencing, a model for the systematic variations of the KPI over the site can be computed. This enables a prediction of behaviour at new locations and yields a statistically more significant detection of anomalous data. It is important to note that the KPI capture expert knowledge; consequently, decisions are not based solely on machine learning; i.e. the machine learning serves as an additional mechanism to detect anomalies possibly overseen by the experts.

3.1 Case Studies

3.1.1 Detection of an element related quality issue

At the beginning, the project manager defines the minimum quality criteria for the compaction of the columns. These are minimum values for amperage, pull-down force and the ratio of pulling and pushing distances of the vibrator for each compaction step. A column is flagged as a quality outlier if it does not fulfil all criteria and needs to be reviewed manually by the project manager (Figure 2).

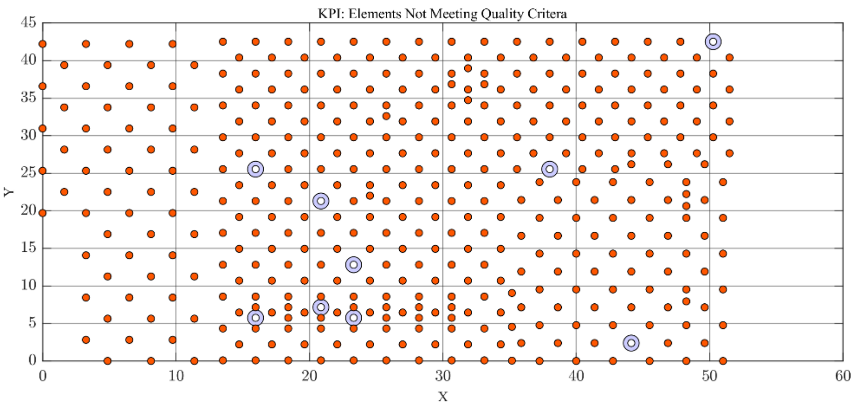

Figure 2. GPS references data: each point corresponds to a produced foundation column. The elements that do not fulfil the quality criteria for compaction are marked with grey circles. These are considered to be outliers require manual evaluation of the corresponding MVTS.

In the current example, all but one, of the flagged outliers were classified as columns with sufficient quality after the manual review. The installation report for the one exception is shown in Figure 3. Whereas low Amperage and Pull-Down-Force values are recognized at a depth of 1-3 m, the pull-out and push-in ratio of the Vibrator movement is within the range of the Quality-KPI (green in Figure 3). However, in the upper meter the pull-push-ratio is also not fulfilled due to exceeding pull-out distances (violet in Figure 3). Consequently, the required execution quality of the column is not achieved. This was detected automatically by the Digital Twin, showing red points at the concerned compaction steps. As a result, the upper part of the column had to be reworked.

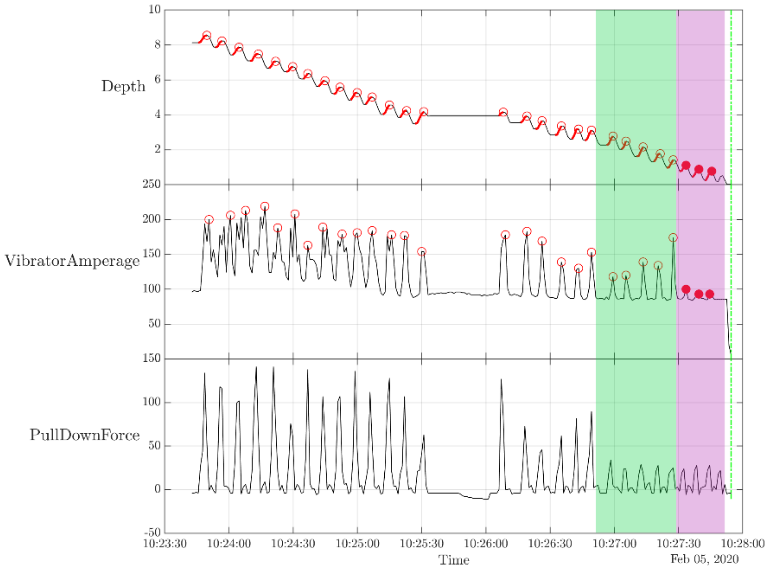

Figure 3. Installation report of a single column in the compaction phase with the analysis of every single compaction step regarding the compaction quality.

3.1.2 Detection of an efficiency issue

For the project illustrated in Figure 4 the estimated shift performance was not reached during execution, however, the reason for the lower performance was not obvious.

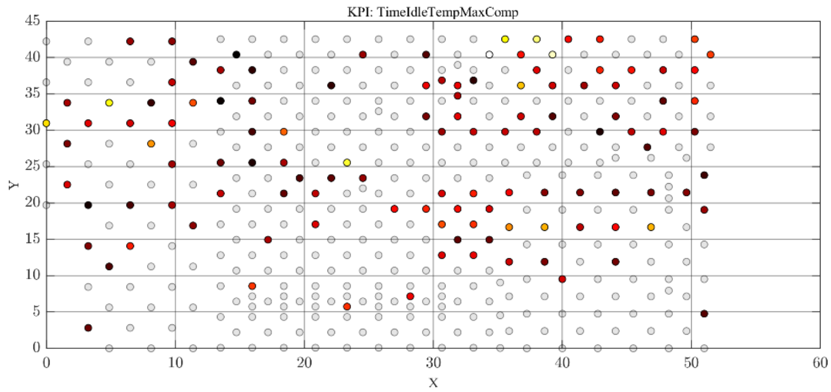

Figure 4. The coloured points correspond to foundation columns where unusual idle times were detected. The machine learning detected that this is a result of overheating of the vibrator.

The Digital Twin detected a correlation between the temperature of the vibrator and idle times during the execution of the columns (Figure 5). It turned out, that the stiffness of the soil was higher than expected, leading to a higher resistance against penetration and thus resulting in an overheating of the vibrator's motor. Idle time was required to avoid this overheating. This led to a loss in production time and a reduction in process efficiency. This hidden lost time was identified reliably in all cases.

The penetration phases of two installation reports from the same site are shown in Figure 6, where the achieved production rate was lower than expected. The evaluation of the KPI did not show any outliers or other reasons for that behaviour. However, the machine learning algorithm identified several outliers. Review of the corresponding installation reports revealed differences in the working behaviours during the penetration phase. For correctly executed columns, the penetration into the bearable soil layer, i.e. when approaching the maximum depth, took ca. 20 seconds (right in Figure 6). The outliers found by the ML showed a significant longer penetration phase into the bearable soil of ca. one minute (left in Figure 6). That means that the rig operator was overfulfilling the required penetration quality and therefore loosing time which was finally leading to a reduced shift performance. As a consequence, a new KPI was defined to describe the quality of the embedding of the column into the bearable soil layer. This can be regarded as a knowledge discovery process.

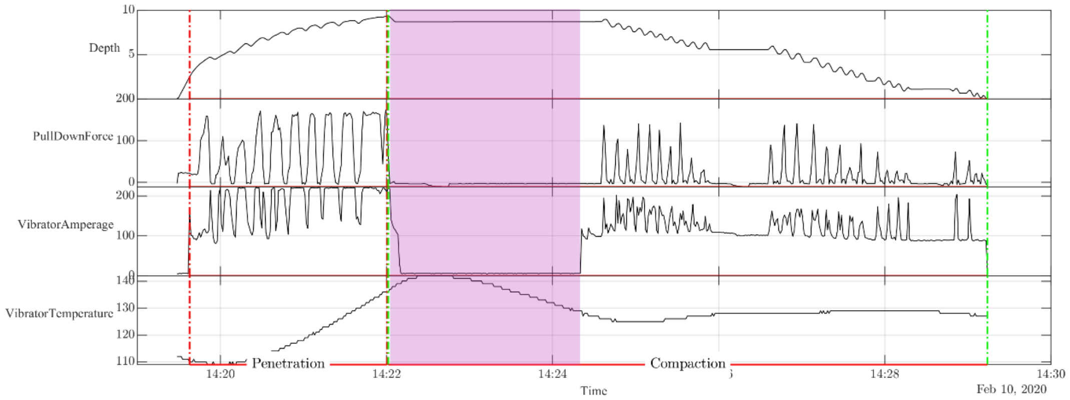

Figure 5. Example installation report exhibiting unplanned Idle time (violet). This was the result of overheating of the vibrator.

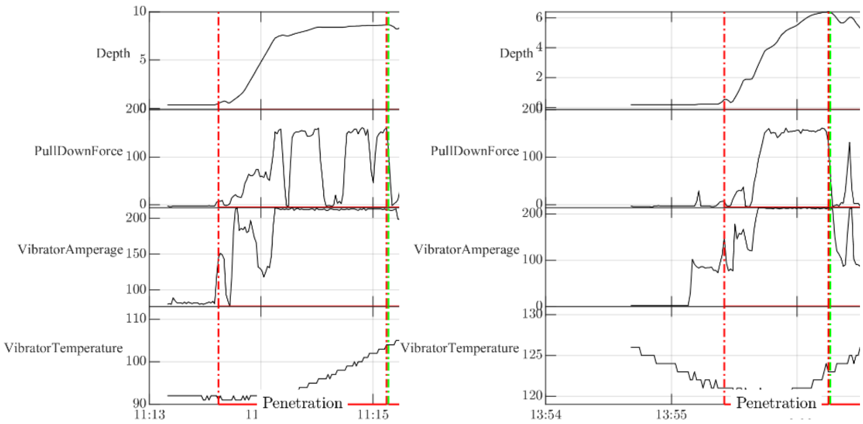

Figure 6. Segments of two installation reports for one and the same site. Left: abnormal case, the operator has overfulfilled the penetration requirement. The required bearing capability of the soil had been reached but penetration was nevertheless continued. Right: Normal operation where the penetration is terminated when the require bearing capacity is reached.

4 OUTLOOK

As a next step the new quality application will be fully integrated into Keller's digital site management system. It will enhance the daily site management routines and support the project and site managers to detect potential quality issues both more reliable and efficient. Also, site or machine related deviations from the planned working procedures, e.g. unusual idle times, will be displayed automatically.

In a next phase, the improved quality application will support the rig operator during execution of the elements. KPI, either pre-defined by the project manager or automatically referenced to the parameters of already executed points, will define the quality criteria for each element. The operator will be informed, in a timely manner, by the rig computer if one or several quality criteria are not fulfilled. This will enable the immediate adjustment of the working procedures. The timely detection of anomalous points permits alleviating measures to avoid finishing a site with low quality issues.

Of course, the implementation of the improved quality application for deep vibro techniques will serve as a role model to develop similar procedures for various other geotechnical techniques, e.g. jet grouting. For any new technique the definition of meaningful KPI will be the biggest effort, but due to the hybrid approach this step will be more and more supported by the results delivered by the ML algorithms.

REFERENCES

Audibert, J., Michiardi, P., Guyard, F., Marti, S. & Zuluaga, M. A., 2022. Do Deep Neural Networks Contribute to Multivariate Time Series Anomaly Detection? ArXiv e-prints.

Baldi, P., 2012. Autoencoders, unsupervised learning, and deep architectures. In Guyon, I., Dror, G., Lemaire, V., Taylor, G., and Silver, D., editors, Proceedings of ICML Workshop on Unsupervised and Transfer Learning, volume 27 of Proceedings of Machine Learning Research, pages 37–49, Bellevue, Washington, USA. PMLR.

Falk, E., Zöhrer, A., Strauch, G. 2011. Entwicklung der Tiefenverdichtung – Von der händischen Datenaufzeichnung zur automatischen Visualisierung. ÖGT, Wien, 2011.

Garg, A., Zhang, W., Samaran, J., Savitha, R. & Foo, C.-S., 2021. An evaluation of anomaly detection and diagnosis in multivariate time series. IEEE Transactions on Neural Networks and Learning Systems, 33(6):2508–2517.

Goodfellow, I., Bengio, Y. & Courville, A., 2016. Deep learning. MIT Press, Cambrige and London.

Graves, A., & Fernandez, S. (2005). Bidirectional Recurrent Neural Networks. In Proceedings of the 22nd International Conference on Artificial Neural Networks (ICANN 2005) (pp. 195-200). Springer, Berlin, Heidelberg.

Hinton, G.E., Rumelhart, D.E., & Williams, R.J. (1986). Learning internal representations by error propagation. In D.E. Rumelhart & J.L. McClelland (Eds.), Parallel Distributed Processing: Explorations in the Microstructure of Cognition (pp. 318-362). Cambridge, MA: MIT Press.

Hochreiter, S., & Schmidhuber, J. (1997). Long short-term memory. Neural Computation, 9(8), 1735-1780.

Khalili-Motlagh-Kasmaei, N., Ninevski, D., O'Leary, P., Winter, V., Zöhrer, A. 2022. A digital Twin for Vibro Ground Improvement. DFI EFFC Conference, Berlin 2022.

Kingma, D. P. & Welling, M., 2013. Auto-Encoding Variational Bayes. ArXiv e-prints.

Makridakis, S., Spiliotis, E. & Assimakopoulos, V., 2020. The M4 Competition: 100,000 time series and 61 forecasting methods. International Journal of Forecasting, 36(1):54–74.

Mavikumbure, H. S., Wickramasinghe, C., Marino, D., Cobilean, V. & Manic, M., 2022. Anomaly Detection in Critical-Infrastructures using Autoencoders: A Survey. In IECON 2022 – 48th Annual Conference of the IEEE Industrial Electronics Society, pages 1–7. IEEE.

Raissi, M., Perdikaris, P. & Karniadakis, G., 2019. Physics-informed neural networks: A deep learning framework for solving forward and inverse problems involving nonlinear partial differential equations. Journal of Computational Physics, 378:686 – 707.

Terbuch, A., 2021. LSTM hyperparameter optimization: Impact of the selection of hyperparameters on machine learning performance when applied to time series in physical systems. Master's thesis, Chair of Automation, Montanuniversitaet Leoben.

Terbuch, A., O'Leary, P. & Auer, P., 2022a. Hybrid machine learning for anomaly detection in industrial time-series measurement data. IEEE International Instrumentation and Measurement Technology Conference (I2MTC), 2022, pages 1–6.

Terbuch, A., Zöhrer, A., Winter, G., O'Leary, P., Khalili-Motlagh-Kasmaei, N. & Steiner, G. 2022b. Quality Monitoring in Vibro Ground Improvement: A Hybid Machine Learning Approach. *Geomechanics and Tunnelling* 10 (4), pp. 366-379. DOI: 10.1002/geot.202200028.

Terbuch, A., O'Leary, P., Khalili-Motlagh-Kasmaei, N., Auer, P., Zöhrer, A. & Winter, V., 2023. Detecting anomalous multivariate time-series via hybrid machine learning. IEEE Transactions on Instrumentation and Measurement.

Zöhrer, A. & Wondre, J. 2012. Neue Entwicklungen und Anwendungen von VibroScan. 2. Symposium Baugrundverbesserung in der Geotechnik, Wien, 2012.