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ORIGINAL

Numerical simulation and process parameter simulation of dam vibration compaction construction

Simulación numérica y simulación de parámetros de proceso de la construcción por compactación vibratoria de presas

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ABSTRACT

Introduction: vibration compaction is also essential in building earth-rock dams because it ensures the density of soil, mechanical stability, and avoids deformation with time. Nevertheless, the definition of internal soil behaviour under dynamic stress cannot be done properly by field data alone, and it is impossible to optimise the vibration frequency, lift thickness, and roller speed.
Method: the rationale behind this research is to unite the numerical simulation with the machine-learning-based prediction to evaluate the performance of vibration compaction and identify the most appropriate construction parameters to use in dam embankment projects. The Dam Vibration Compaction Dataset captures realistic field, lab, machine, and simulation-based parameters for earth-rock dam compaction, comprising 25 features. Data Preprocessing entailed normalization of data and filtering of noisy sensor readings.
Results: internal stress distribution and densification behavior in soil were simulated using a coupled soil-vibration dynamic model based on the Finite Element Method. Simultaneously, a Scalable Random Vector Machine algorithm, combining the Scalable Support Vector Machine and the Random Forest algorithms, was created to forecast compaction quality under varying parameters.
Conclusions: the FEM+SRVM model, implemented using Python, demonstrated a high level of prediction, with the most effective parameters being the vibration frequency of 30 Hz and Root Mean Square Error of 0,0083. The combined numerical and ML method enables a potent means of dam vibration compaction analysis and optimisation to remove the trial-and-error method and increase the reliability and quality of construction.

Keywords: Construction; Dam Vibration; Earth-Rock; Pressure; Soil Parameter; Scalable Random Vector Machine (SRVM).

RESUMEN

Introducción: la compacpor vibración también es esencial en la construcción de presas de tierra y roca, ya que asegura la densidad del suelo, la estabilidad mecánica y evita la deformación con el tiempo. Sin embargo, la definición del comportamiento interno del suelo bajo un esfuerzo dinámico no puede hacerse correctamente solo con los datos de campo, y es imposible optimizar la frecuencia de vibración, el espesor de elevación y la velocidad del rodillo.
Método: la justificación detrás de esta investigación es unir la simulación numérica con la predicción basada en aprendizaje mecánico para evaluar el rendimiento de la compactación por vibración e identificar los parámetros de construcción más adecuados para su uso en proyectos de repres. El conjunto de datos de la compacde la vibración de la presa captura parámetros realistas de campo, laboratorio, máquina y basados en

la simulación para la compacde la presa tierra-roca, que comprende 25 características. El preprocesamiento de datos implicla normalización de los datos y el filtrado de las lecturas de los sensores ruidosos.
Resultados: se simularon la distribución de tensiones internas y el comportamiento de densidel suelo mediante un modelo dinámico de sol-vibración acoplbasado en el método de elementos finitos. Simultáneamente, un algoritmo escalable Random Vector Machine, que combina el Scalable Support Vector Machine y el Random Forest, fue creado para predecir la calidad de compacbajo parámetros variables.
Conclusiones: el modelo FEM+SRVM, implementado usando Python, demostró un alto nivel de predicción, con los parámetros más efectivos siendo la frecuencia de vibración de 30 Hz y Error cuadrático medio de 0,0083. El método numérico combinado y el método ML permite un potente método de análisis y optimización de la compactación de la vibración de la presa para eliminar el método de ensayo y error y aumentar la fiabilidad y la calidad de la construcción.

Palabras clave: Construcción; Vibración de la Presa; Tierra-Roca; Presión; Parámetro del Suelo; escalable Random Vector Machine (SRVM).

INTRODUCTION

Vibration compaction is a critical process in earth-rock dam engineering, as embankment layers must achieve sufficient density, mechanical stability, and long-term resistance to deformation to ensure structural safety and durability.[1] During construction, heavy vibratory rollers transmit dynamic energy into soil layers, causing soil particles to rearrange into a denser configuration. The effectiveness of this process depends on several interacting parameters, including soil type, moisture content, lift thickness, vibration frequency, amplitude, roller speed, and the number of roller passes.[2] These parameters influence vibration penetration depth, pore pressure evolution, and the dynamic stress-strain response of the soil mass.[3] As illustrated in figure 1, vibratory rollers generate dynamic stress components within the soil, which play a key role in optimizing dam compaction performance.

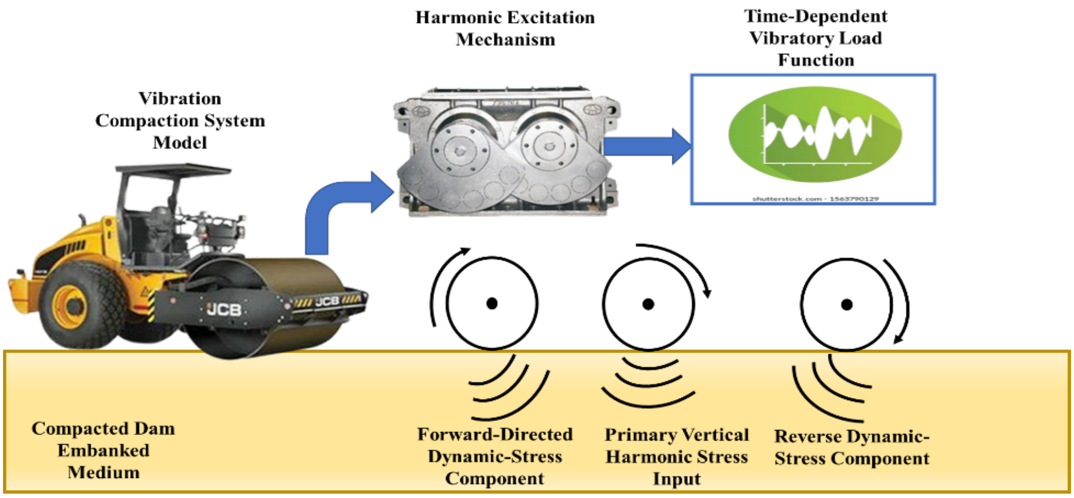

Figure 1. Vibration roller generates dynamic stress components enabling accurate modelling and optimization of dam compaction performance

Compaction quality is vital in dam construction, yet conventional quality control largely relies on in situ density tests, post-compaction inspections, and empirical adjustment of roller parameters.[4] These approaches are labor-intensive, time-consuming, and heavily dependent on operator experience. They also fail to directly capture internal stress distribution and soil densification, often resulting in inconsistent compaction outcomes.

To address these limitations, numerical and computational methods have been increasingly applied to study soil-vibration interactions. Techniques such as the finite element method (FEM), discrete element modeling, and dynamic soil-structure interaction simulations enable detailed analysis of stress propagation, vibration energy transfer, and effective compaction depth.[5] Concurrently, advances in sensing technologies allow real-time monitoring of roller-soil interactions. Data-driven approaches, including logistic regression, Naive Bayes classifiers, artificial neural networks, and surrogate modeling, have also been employed to predict compaction performance and optimize operational parameters.[6]

However, each method has limitations. Numerical simulations, though physically interpretable, are computationally intensive and unsuitable for real-time control. Traditional machine learning requires large labeled datasets and struggles with the highly nonlinear, dynamic behavior of soil–vibration systems.[7] Even deep learning models, while more accurate, are computationally expensive, difficult to interpret, and fail to integrate physical soil mechanics fully, limiting their reliability for in-depth compaction analysis in dam construction.[8]

Several studies have addressed specific aspects of vibration compaction through either numerical or data-driven approaches. Numerical investigations have focused on soil–structure interaction and vibration behavior. For example, a three-dimensional viscous fluid model was used in [9] to simulate saturated sandy soil in a cylindrical gravity dam, showing a deformation reduction of approximately 20 % under seismic excitation compared with conventional designs. A detailed numerical model describing the interaction between vibrating drums and underlying soil was presented in [10], considering soil conditions ranging from loose to dense particulate states.[11] Similarly, a three-dimensional FEM model of a vibrating axle interacting with soil was developed in [12], providing insights into stress distribution and overlap length requirements for uniform compaction quality.

Other studies have explored inverse analysis and vibration detection techniques. A hybrid least squares QR (LSQR) method was proposed in [11] to address ill-posed vibration load detection problems, achieving improved accuracy and noise resistance. DEM-based studies have examined particle-scale mechanisms of vibration compaction, including slag materials with varying gradations[13] and soil–rock mixtures with different homogeneity levels,[14] contributing to improved filler selection and subgrade performance prediction.

In parallel, machine learning–based approaches have been developed for compaction quality evaluation. A gradient boosting decision tree (GBDT) model was used in [15] to estimate earth-rock dam compactness, achieving a root mean square error of less than 0,041 g/cm^3. An improved firefly optimization–based random forest (IFO-RF) model was introduced in [16], demonstrating reliable real-time prediction of compaction performance with a mean squared error of 0,0000602. Additionally, an Elman neural network optimized using adaptive simulated annealing particle swarm optimization (ASA-PSO) was proposed in [17] to evaluate dynamic compaction density for sand–gravel materials with wide particle size distributions.

Although these studies have significantly advanced understanding and prediction of vibration compaction, they generally address numerical simulation or machine learning prediction in isolation. Numerical models lack adaptability and real-time optimization capability, while machine learning models lack embedded physical mechanisms and generalizability across varying soil and construction conditions. This highlights a clear research gap: the need for a hybrid framework that integrates physics-based numerical simulation with data-driven machine learning to achieve accurate, interpretable, and practical compaction optimization.

To address this gap, this research proposes an integrated numerical and machine learning framework for dam vibration compaction analysis and optimization. A finite element–based dynamic soil–vibration model is developed to simulate internal stress distribution, pore pressure evolution, and soil densification behavior under dynamic loading. Simultaneously, a scalable random vector machine (SRVM), integrating scalable support vector machine and random forest models, is constructed to predict compaction quality using both simulation outputs and field measurements. The main contributions of this work are summarized as follows:

- Developed an integrated numerical simulation and ML model (FEM + SRVM) for dam vibration compaction analysis.
- Collected the Dam Vibration Compaction Dataset, including field compaction measurements, moisture content, soil laboratory tests, and roller machine parameters.
- Designed a FEM-based dynamic soil–vibration model to simulate internal stress distribution and soil densification behavior.
- Proposed an SRVM combining a Scalable SVM and a Random Forest for accurate compaction quality prediction
- Achieved a better MSE of 6,90, validating the model against field compaction results.

Problem statement

Although the current methods of numerical simulation and ML in dam and soil compaction have improved, they still have some limitations in the accurate prediction of internal soil behavior during vibration under dynamic conditions, optimization of roller parameters, and heterogeneous soil-rock mixture. Viscous fluid modeling[9] and finite element simulations[12] can be difficult to integrate with real-time parameter optimization, whereas LSQR[11] is limited by small data or sensitivity to noise. Thus, an integrated FEM and SRVM system is offered that would address these limitations and offer precise, real-time, and optimal predictions of vibration compaction.

Materials and Methods field data, soil tests, preprocessing, FEM modeling, and SRVM prediction were applied in Section 2. Section 3 results and discussion, simulations matched field behavior, and highlighted key parameters. In section 4 conclusion integrated the FEM–SRVM approach, optimized compaction, and improved construction efficiency.

METHOD

The research combines both numerical simulation and ML prediction to optimize the process of dam vibration compaction. Preprocessing of field and laboratory data in the form of normalization, calibration, and noise filtering was carried out to determine soil properties, moisture content, and roller parameters. An SRVM was estimated to forecast the quality of compaction, and a FEM dynamic model was used to simulate stress distribution and densification of soil. The FEM+SRVM model has found optimal vibration frequency, roller speed, and lift thickness, which are consistent with the field outcomes. Figure 2 shows the Complete workflow predicting compaction quality and soil behavior using FEM-ML integration.

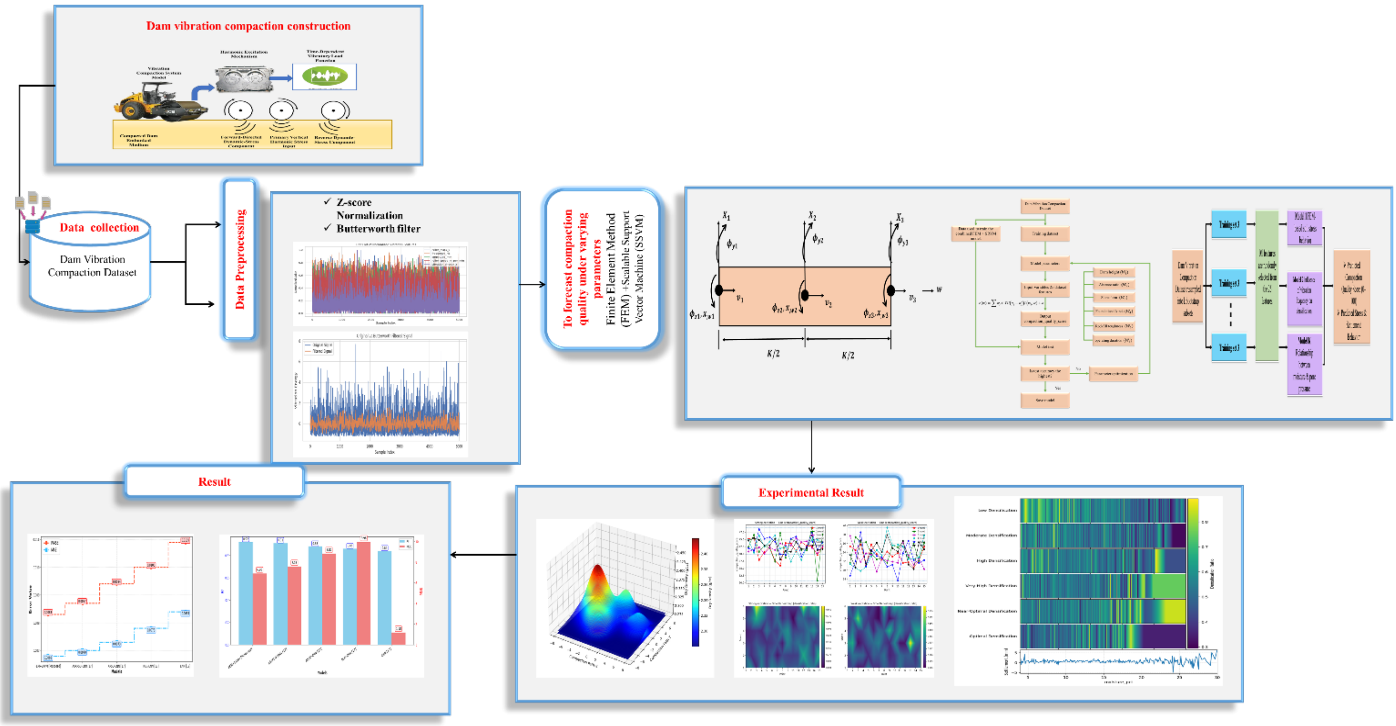

Figure 2. Integrated FEM-ML processes compaction data to predict soil behavior and optimise dam vibration performance

FEM + SRVM simulate soil behavior and predict optimal vibration compaction parameters, ensuring efficient, accurate dam construction

The FEM and SRVM are integrated in the research of dam vibration compaction to maximize the construction parameters. The dam embankment is modeled in detail, with FEM, into a numerical model that employs dynamic vibration loads to simulate the behavior of the soil. Through the method, the soil is broken down into small finite elements, and roller stresses are applied to an element. FEM determines the internal stress distribution, shear strain formation, pore pressure response, and densification patterns, which are difficult to measure in the field.

The Finite Element Method (FEM) numerically simulates internal soil stress and densification during vibration compaction

FEM simulates vibration compaction by dividing the soil layer into finite elements, applying roller-induced dynamic loads, and calculating stress waves, deformation, and density changes. It reveals internal soil behavior, helping evaluate vibration penetration depth and determine optimal compaction parameters for dam construction. A linear polynomial interpolated variable $\varphi_j(w)$ is used to derive the changes in the unknowns v_p, ϕ_z and ϕ_y, while a Hermite-cubic polynomial interpolated functional $\psi_j(w)$ is used to estimate x_p. The adjustments that are averaged are stated as follows within the element in equation 1:

$$
\begin{aligned}
v_p(w,s) &= \textstyle\sum_{j=1}^{3} \psi_j(w) v_j \qquad (1)\\
x_p(w,s) &= \textstyle\sum_{j=1}^{6} \varphi_j(w) x_j\\
\phi_z(w,s) &= \textstyle\sum_{j=1}^{3} \psi_j(w) \phi_{zj}\\
\phi_y(w,s) &= \textstyle\sum_{j=1}^{3} \psi_j(w) \phi_{yj}
\end{aligned}
$$

Where v_j, x_j ϕ_{zj} and ϕ_{yj} are modified nodal displaced parameters, the associated nodal positions are designated by the suffix j, and the shape variables $\psi_j(w)$ and $\varphi_j(w)$ are provided in the Appendix. $v_p(w,s)$ predicted vibration velocity at frequency, $x_p(w,s)$ predicted displacement at frequency, $\phi_z(w,s)$ predicted rotational displacement, $\phi_y(w,s)$ predicted rotational displacement. The following matrix equations for free vibration and x^2 bending are obtained by substituting equation 2 into equation 3 and applying the outcome in equation 1:

$$[L - x^2 N]\Delta = 0 \quad (2)$$

$$[L - M_p H]\Delta = 0 \quad (3)$$

Where L is the vector of undetermined parameters, N is the mass matrix, H is the geometrical flexibility structure, and Δ is the rigidity vector. The bending load and natural periodicity are denoted by M_p and correspondingly. The supplement contains the elements of these vectors; it simulates internal soil changes to optimize compaction parameters accurately. Figure 3 shows the nonlinear mappings that transform inputs to model soil behavior during vibration compaction.

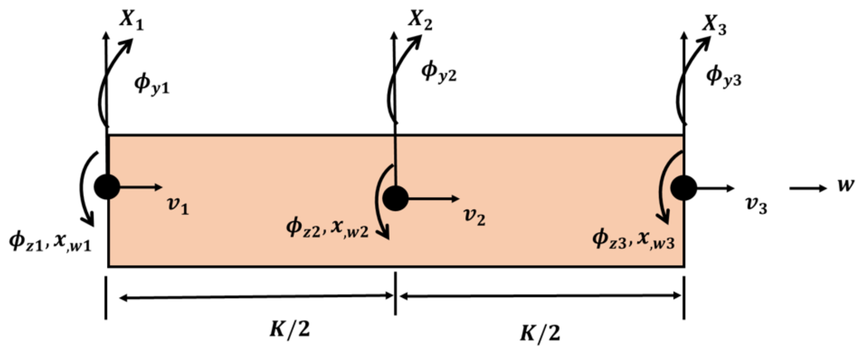

Figure 3. Nonlinear transformations model soil response and compaction behaviour to support FEM in dam construction

v_1, v_2, v_3, are transformed by nonlinear mapping functions $\phi z^1, x, w^1$, $\phi z^2, x, w^2$, $\phi z^3, x, w^3$ to generate feature outputs used for further modelling, x_1, x_2, x_3 operational variable, ϕ_{y1}, ϕ_{y2}, ϕ_{y3} nonlinearly transformed to capture soil behavior under dynamic loading.

SRVM Framework for Predicting and Optimizing Dam Vibration Compaction Parameters

The SRVM serves as the core predictive engine in the hybrid framework. It combines a Scalable Support Vector Machine (SSVM) for modeling nonlinear relationships and a Random Forest (RF) module for robustness. FEM-derived soil features and field-measured roller parameters are input to SRVM, which maps these features into a high-dimensional space using mixed kernel functions (polynomial + RBF) to capture complex patterns. The SSVM predicts compaction quality, while the RF validates and refines these predictions, reducing sensitivity to noise and data variability. The combined SRVM output identifies optimal vibration frequency, roller speed, and lift thickness, enabling accurate, interpretable, and reproducible parameter optimization for dam vibration compaction.

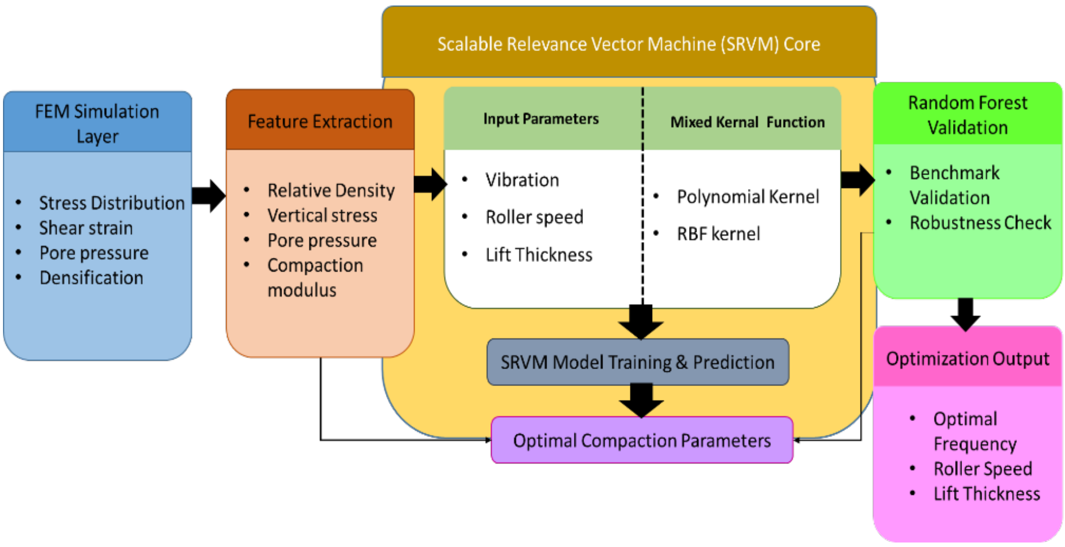

Figure 4. SRVM-Based Hybrid Framework with FEM Feature Integration for Dam Compaction Optimization

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Schematic showing FEM simulation layer generating soil response features, SRVM core performing mixed-kernel regression, Random Forest validation, and final output of optimal compaction parameters.

Scalable Support Vector Machine (SSVM) handles high-dimensional simulation and field data efficiently.

SSVM classifies and predicts compaction quality by learning relationships between vibration parameters (frequency, speed, lift thickness) and soil response features, helping identify optimal parameter combinations for accurate dam vibration compaction performance. By mapping the collected data to a hyperspace and utilizing kernel operations to solve the nonlinear regression issue, the SSVM algorithm forecasted the dam construction. The variables W_1 to W_6 represent grouped feature vectors derived from the dataset features. Each W_j summarizes related soil, roller, FEM, or compaction response variables to simplify the SSVM equations while maintaining full consistency with the dataset. These include dam height (W_1), absence ratio (W_2), slope form (W_3), foundational kinds (W_4), rockfill toughness (W_5), and operating duration (W_6), it also set the (z) as the label, as the inputs, the output, and input parameters have the following mathematical mappings in equation 4:

$$z = e\{W_1, W_2, W_3, W_4, W_5, W_6\} \quad (4)$$

The regression equation for the sampling set $e(w)=x.w$ is as follows in equation 5:

$$e(w) = x.w + a \quad (5)$$

Where is the intercepting location, and $x = (x_1, x_2, \ldots, x_n)^S$ is the weight factor.

To convert the aforementioned convex quadratic optimization issue into a pairwise issue, it employs the Lagrange coefficients α_j-α_j^*, enabling accurate parameter optimization and reducing the need for trial-and-error in dam construction. The regression polynomial that is ultimately obtained is equation 6:

$$e(w) = \sum w_j \in TU\left(\alpha_j - \alpha_j^*\right)L\left(w_j, w\right) + a \quad (6)$$

Where the kernel functional (KF) is denoted by $L(w_j,w)$. Kernel values determine the model's effectiveness, $\sum wj$ and $\in$ various sample data should be chosen for the associated adaptive kernel values. Then, TU it is also essential to optimize the necessary parameters for the chosen kernel operations.

Typically, the SSVM kernel is the polynomial component or Radial Basis Function kernel (RBF), which appears below accordingly to equations 7 and 8.

$$L(w, w') = ((w, w') + d)^c \quad (7)$$

$$L(w, w') = \exp\left(\frac{-\|w, w'\|^2}{2\sigma^2}\right) \quad (8)$$

Where $2\sigma^2$ is the RBF KF variable, d is the poly kernel coefficient, c is the penalty value, and w and w' are the input information. Choosing an appropriate KF is the main goal of model improvement $L(w,w')$. It creates a smoothly merged combined KF relying on the poly functional and RBF, KF due to the high dispersal and high vulnerability of several elements of the dams. The benefits of both KFs L_{mix} were combined in this combined kernel in equation 9:

$$L_{mix} = \eta L_{poly} + (1 - \eta) L_{qae} \quad (9)$$

Where η is the combination weight, L_{qae} is the Gauss basis coefficient, and L_{poly} is the polynomial KF. To employ the combined KF for various data sample information, the weighting factors are altered to change the amplitude of the effect of the two distinctive KFs that learns patterns between vibration frequency, roller speed, lift thickness, moisture content, and soil response features such as dynamic stress, pore pressure, and compaction modulus. Figure 5 shows the flowchart predicting compaction quality and optimizing parameters for efficient dam construction.

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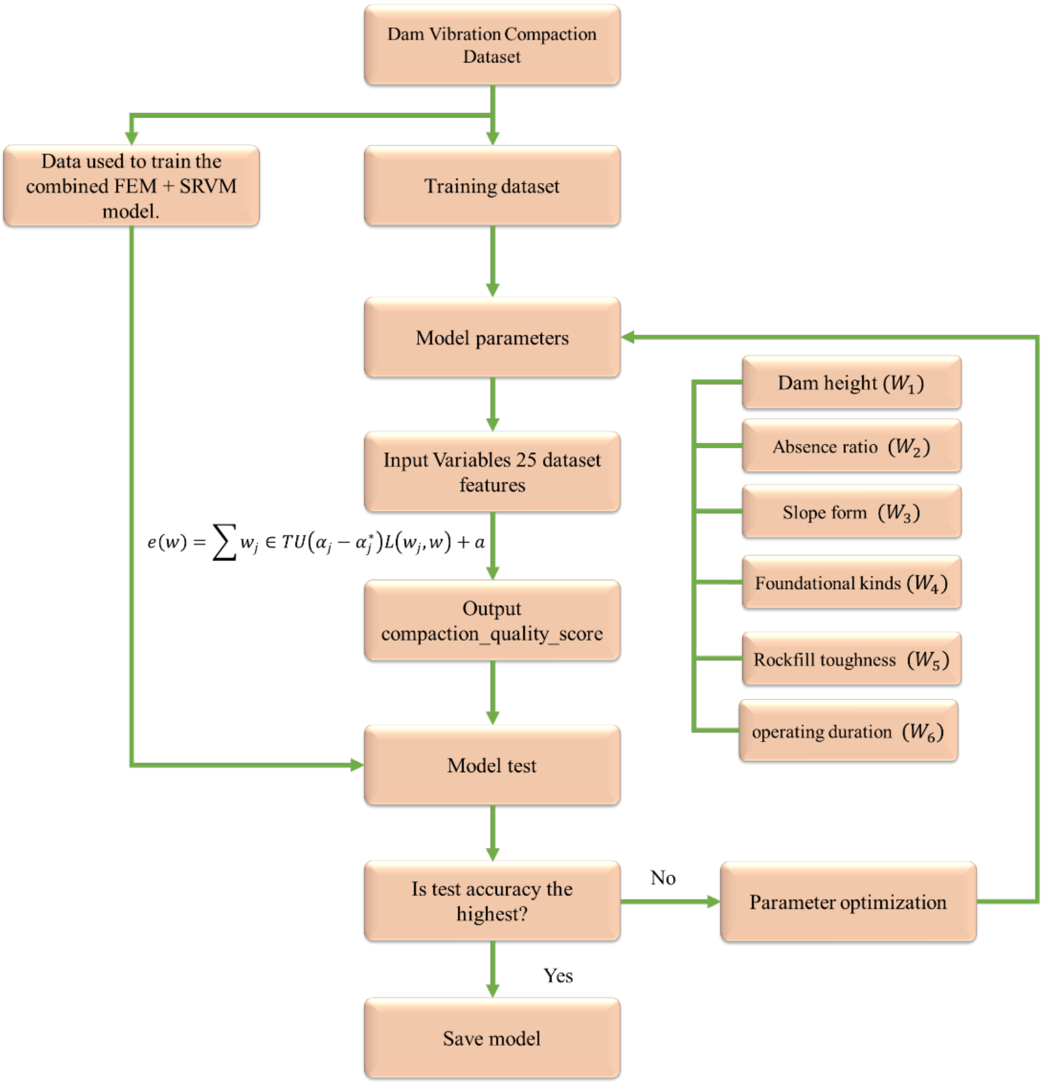


Figure 5. SSVM workflow integrating dataset features to optimize parameters and accurately predict dam compaction quality

Random Forest (RF) captures non-linear relationships and is robust to noisy data

RF predicts dam compaction quality by learning patterns from FEM-simulated and field-measured features. The input features include soil properties, roller operating parameters (speed, vibration frequency, lift thickness), and FEM-derived soil response features, while the output label Z represents compaction quality, the main target of this study. RF builds an ensemble of decision trees (DTs) to capture non-linear relationships between these inputs and compaction quality. Each tree evaluates how roller parameters and soil characteristics influence soil densification.

RF builds an ensemble of decision trees to capture non-linear relationships between these inputs and compaction quality. Each tree evaluates how roller parameters and soil characteristics influence soil densification. The computational output of the l-th decision tree is denoted as $g_l(W)$, where W represents the input feature vector. Assume that the RF's computational classifier is $g_l(W)$, where is the number of DTs in the

RF, $bu_l J$ is the output result produced by a single classifier for the input matrix i, and every classifier's sample set is arbitrarily selected from the original information set $nh(W,Z)$, subject to an arbitrary distribution. Z represents the matching classification outcome for the training set. Each tree evaluates how roller speed, lift thickness, and vibration frequency influence soil densification follows in equation 10:

$$nh(W,Z) = bu_l J(g_l(W) = Z) - max bu_l J(g_l(W) = i)(i \neq Z) \qquad (10)$$

OF^* is an indication variable that quantifies the degree to which the number of accurate classifications exceeds the number of incorrect classifications; is the classifier's activation times. The interval parameter's mean is denoted by $0_{W,Z}$. The model classification confidence level decreases with decreasing interval parameter.

The model's quality is reflected in the generalization error (GE), which can display the model's degree of prediction using data other than the trained set, effective for modeling complex, non-linear soil behavior and optimizing dam vibration compaction parameters. The classifier set's GE is described as follows:

$$OF^* = O_{W,Z}(nh(W,Z) < 0) \quad (11)$$

Calculating the RF, Generalization Error (GE):

O is the connection among the classifier set, where $(nh(W,Z)$ is the Constraint (or feasibility) function that represents the normalized or nonlinear system DT responsive to independent and identically distributed. The RFs' classification effectiveness decreases with increasing tree-to-tree correlation.

Out-of-bag data (OOB) is the portion of the data that is not chosen during the bootstrapping procedure, which necessitates self-sampling for the creation of every DT. These data can be utilized for model validation because they weren't used to generate the algorithm. It is ideal for improving dam construction efficiency and reducing trial-and-error decisions. Figure 6 shows the bootstrap-trained models predict compaction quality and soil behavior for optimization.

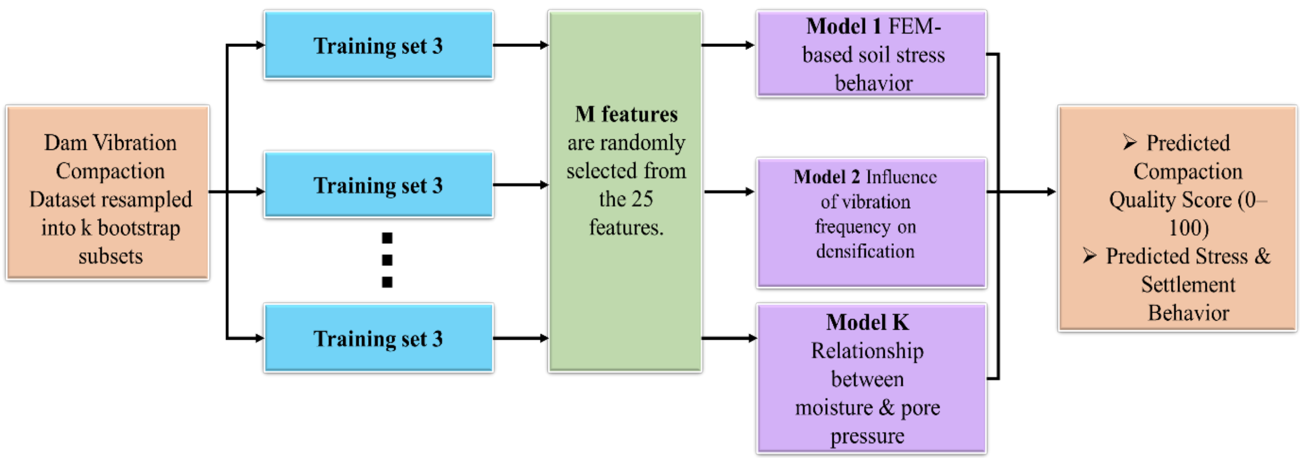


Figure 6. RF resampling features to predict compaction quality and soil behavior for optimal dam construction

RESULTS

The experimental setup used a vibratory roller equipped with onboard sensors, triaxial accelerometers, pore-pressure transducers, and moisture probes to record dynamic soil response during compaction. Numerical simulation was performed using FEM software (Abaqus), while Python-based SRVM models were used for ML prediction and parameter optimization.

The Dam Vibration Compaction Dataset contains 25 features representing soil properties, laboratory parameters, roller machine settings, and FEM-derived dynamic responses for each compaction event. It includes soil type, moisture, density, fines, Atterberg limits, cohesion, friction angle, permeability, vibration frequency, amplitude, roller speed, lift thickness, stress transfer, pore pressure, settlement, and densification ratio. Figure 7 visualizes soil and roller types on the influence of compaction dataset features.

To train the SRVM model, features were extracted from both FEM simulations and experimental measurements. These features represent soil properties, roller parameters, and FEM-derived dynamic responses for each compaction event. Table 1 summarizes the 20 input features used for model training. This explicit listing ensures reproducibility and clarifies which FEM outputs were incorporated into the ML model.

Table 1. Features extracted from FEM simulations and experimental measurements used for SRVM training

Feature No.	Feature Name
1	Soil type
2	Moisture content (%)
3	Dry density (g/cc)
4	Percent fines (%)
5	Liquid limit (%)
6	Plasticity index

7	Cohesion (kPa)
8	Friction angle (°)
9	Permeability (m/s)
10	Roller mass (t)
11	Vibration frequency (Hz)
12	Vibration amplitude (mm)
13	Roller speed (m/min)
14	Lift thickness (cm)
15	Roller type
16	Vibration energy
17	Maximum stress (kPa)
18	Peak pore pressure (kPa)
19	Settlement (mm)

Features 16–20 are directly extracted from FEM simulations, while features 1–15 represent soil and roller parameters. Together, they form the input dataset for the SRVM model to predict compaction performance and optimize parameters. To prevent data leakage caused by temporal and spatial dependencies between roller passes and dam areas, the dataset consisting of 5000 records (simulated and field measurements) was divided by soil type into training (70 %), validation (15 %), and test (15 %) subsets. In addition, a 5-fold time-series cross-validation strategy was applied during SRVM model training, where earlier construction sequences were used for training and later sequences for validation. This ensured a robust assessment of model generalization to unseen compaction stages. This partitioning strategy ensures that the model is trained on diverse compaction scenarios while maintaining an unbiased assessment of predictive performance.

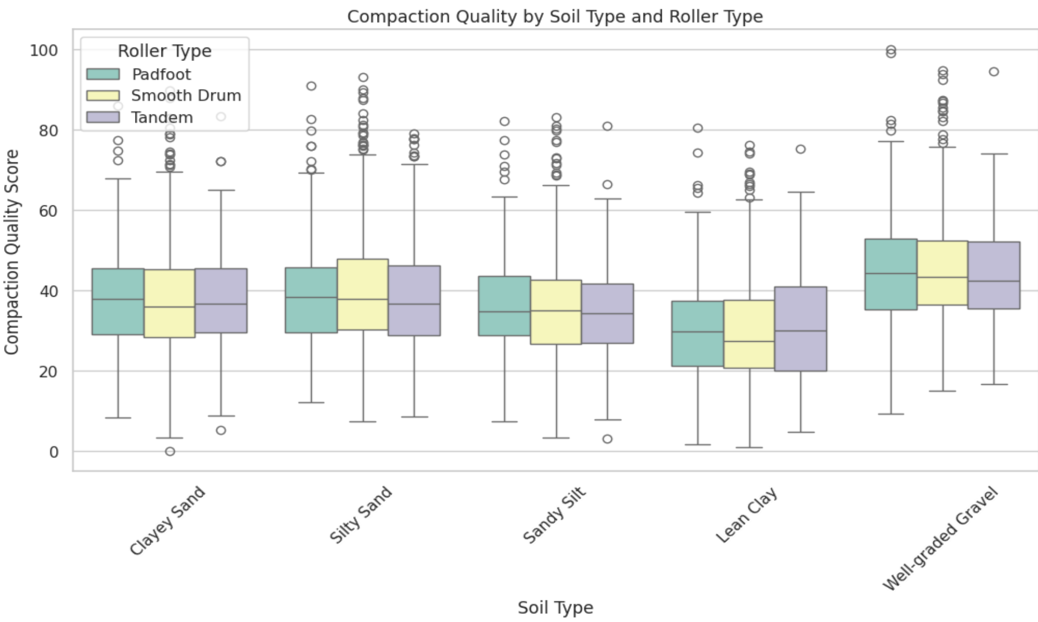


Figure 7. Compaction features illustrate parameter-driven quality differences across multiple soil categories and roller configurations

Source. https://www.kaggle.com/datasets/ziya07/dam-vibration-compaction-dataset

Z-score normalization preprocessed each soil, vibration, and machine-parameter value into a standardized score by centering data around zero and scaling by variability. This process ensures consistent feature ranges, reduces outlier impact, and improves simulation ML model stability in dam vibration compaction analysis. Z-score normalization is a normalization technique based on the information's mean (mean value) and standard deviation (standard deviation). If the real lowest and maximum values of the data are unknown, this method is quite helpful, expressed as equation 12. Figure 8 shows normalized vibration feature fluctuations across samples for compaction analysis. The parameters of the scalable random vector machine were optimized using a grid search approach. Kernel widths were tested from 0,1 to 1,0, and regularization values from 0,01 to

1,0. The optimal combination was selected based on minimizing the root mean square error on the validation dataset, ensuring the best predictive accuracy for compaction quality.

$$W_{new} = \frac{W-\mu}{\sigma} = \frac{W-mean\,(W)}{StdDev\,(W)} \quad (12)$$

W_{new} = The updated value derived from the normalized outcomes.
W = Outdated value.
μ = Average population.
σ = Amount of the standard deviation.

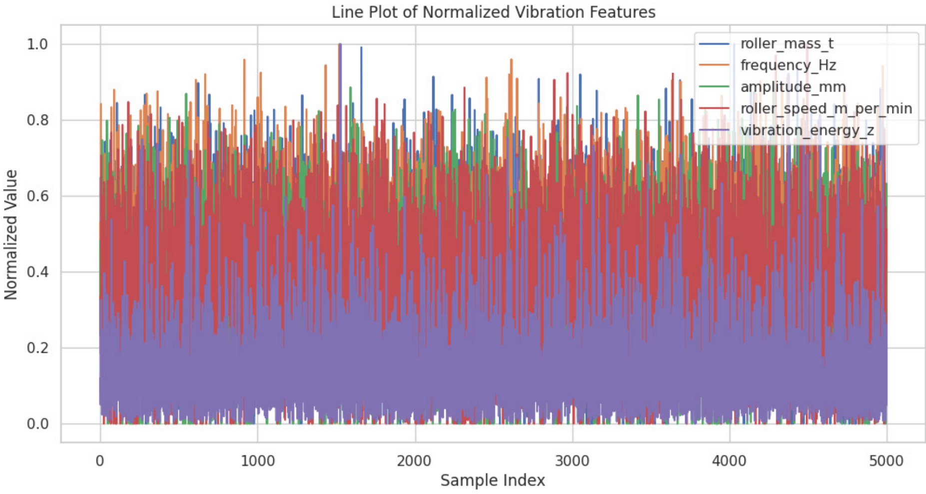


Figure 8. Normalized vibration features reveal dynamic variations in roller mass, frequency, amplitude, speed, and energy

Butterworth filter, used in dam vibration compaction simulation, removes noise from sensor data by applying a smooth, flat frequency response. It filters acceleration, stress, and pore-pressure signals, $H(\omega)$ keeping real vibration patterns while eliminating high-frequency noise for accurate FEM-ML analysis shown in equation 13.

$$H(\omega) = \frac{1}{1+\varepsilon^2\left(\frac{\omega}{\omega_O}\right)^{2m}} \quad (13)$$

Where is the filter rank, ε^2 is the cut-off rate is the correction factor. ω/ω_o normalized frequency ratio raised to the power of *2m*. The Butterworth filter has a major advantage over other filters since it exhibits monotonic properties and the simplest frequency behavior in the passband. Its maximally flat response preserves true soil-roller interaction patterns, improving the accuracy of numerical simulation. Figure 9 shows noise reduction by comparing the original and Butterworth-filtered vibration energy signals.

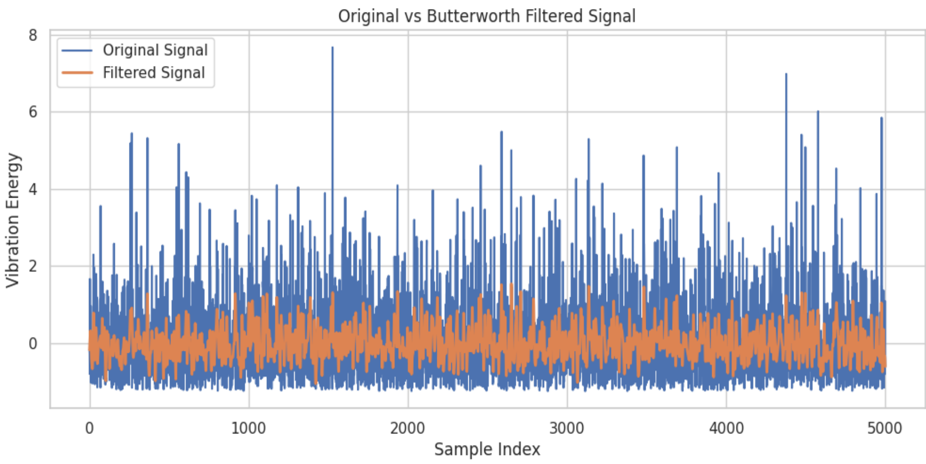


Figure 9. Butterworth filtering smooths the vibration energy signal, reducing noise and highlighting essential compaction trends

Figure 10 compares the quality of compaction and peak pore pressure between various passes of vibration and lift stages. The difference in peaks and stability patterns can be used to demonstrate the effect of the different frequencies and lift conditions and their effects on the soil response. These findings can be directly related to the modeling of dynamic soil behavior and the application of FEM+ SRVM towards the determination of the best vibration parameters to enhance the performance of dam compaction and construct stability.

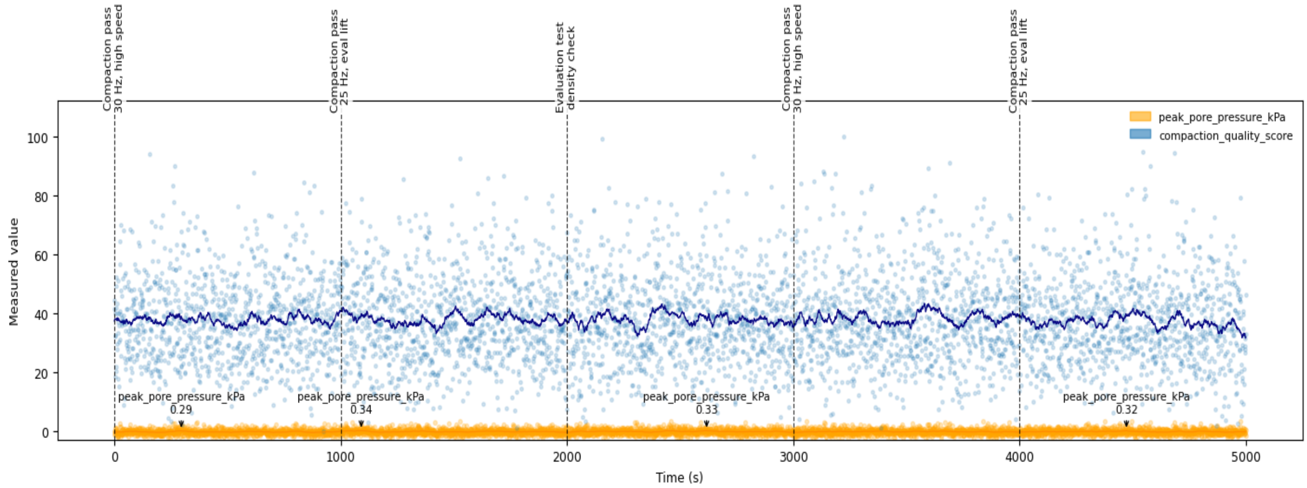


Figure 10. Time-series comparison shows compaction quality and pore pressure responses across multiple vibration passes and lift stages

Figure 11 visualization is a compare-and-condition analysis of the density between diverse soil moisture levels, and it obtains insights into the efficiency of compaction in dam construction. Every heatmap band presents the effect of moisture on the densification ratio, and the bottom plot follows the settlement behavior. These patterns combined can locate areas of moisture where compaction is optimal, which serves the purpose of modelling the FEM+ SRVM model in predicting and optimising vibration parameters to enhance dam embankment stability.

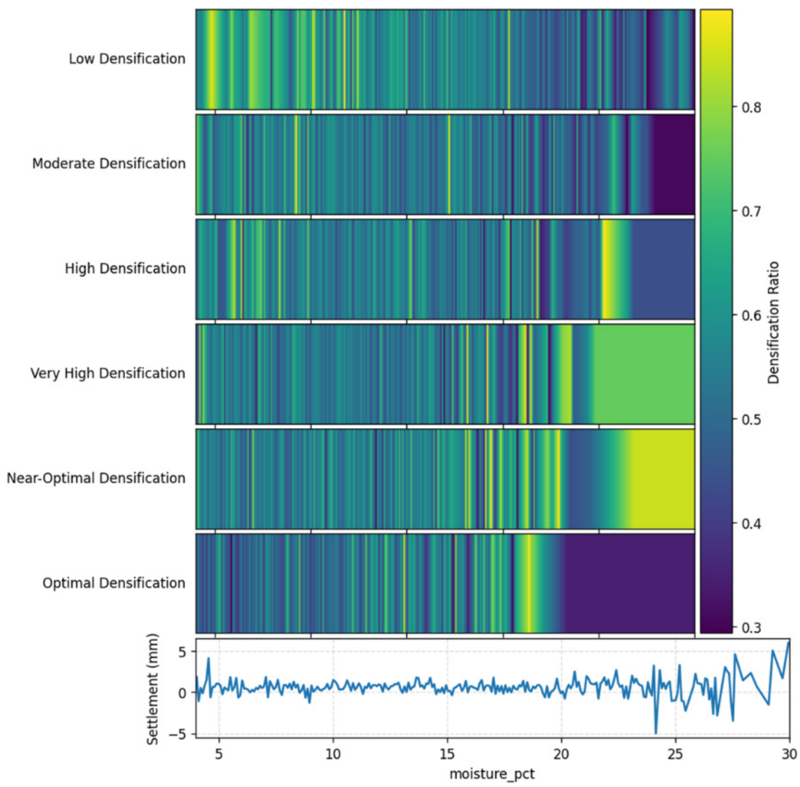
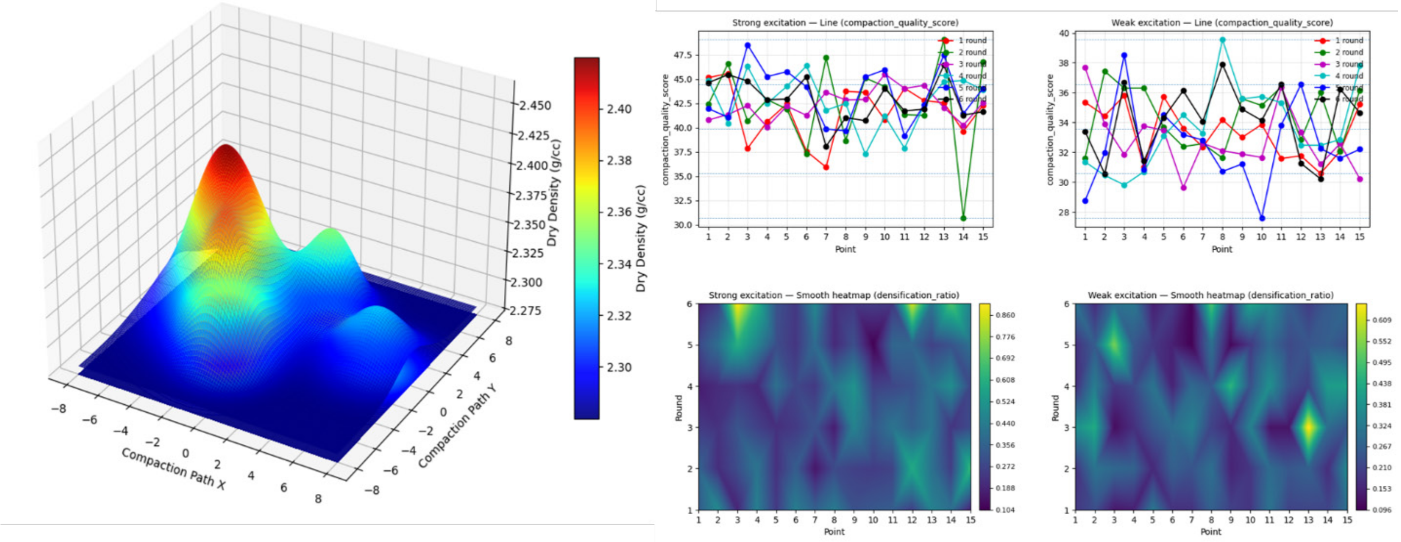


Figure 11. Moisture-driven densification patterns supporting FEM+SRVM optimisation for achieving optimal dam vibration compaction performance

Figure 12 (a) illustrates the spatial distribution of dry density along the compaction path, revealing zones of higher densification influenced by vibration energy and soil response. Figure 12 (b) compares strong and weak excitation patterns across multiple passes, showing their effects on compaction quality and densification ratio. Together, these insights support using FEM+SRVM to optimize dam compaction parameters.



(a) **(b)**

Figure 12. Visualizing (a) spatial densification patterns and (b) excitation effects to support simulation-driven optimization of dam compaction parameters

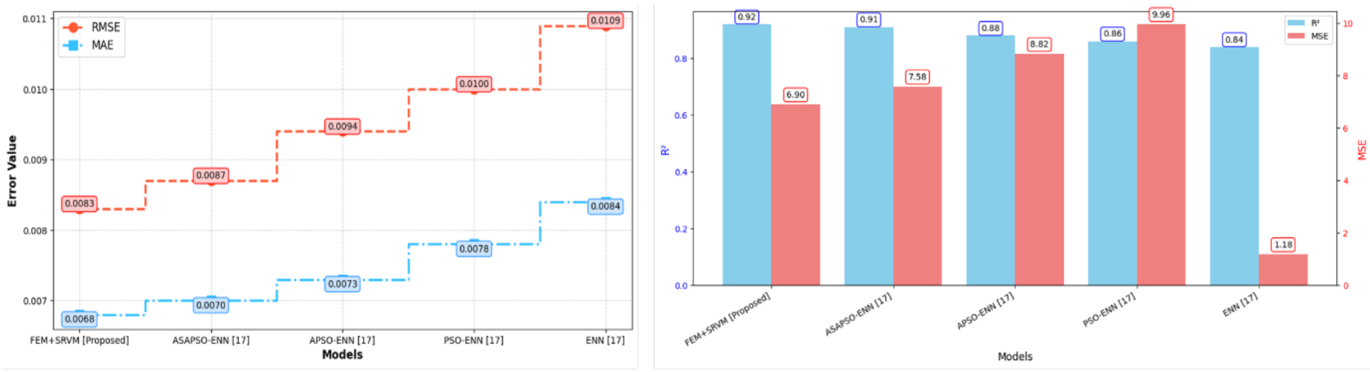
R^2, MSE, RMSE, and Mean Absolute Error (MAE) are used to determine the accuracy of the models in predicting the quality of compaction. R^2 is used to make the prediction of the model against the actual field data in determining the quality of compaction. MSE is a measure of the mean squared error that exists between the predicted and actual values of compaction. RMSE, which is the error in the same unit as the measurement of compaction. MAE is a calculation of the average absolute distance between real compaction results and the predicted compaction results, regardless of the direction of the error.

Table 2. Model performance comparison supporting accurate prediction and optimization of vibration compaction parameters in dam construction projects

Models	R^2	MSE	RMSE	MAE
FEM+SRVM [Proposed]	0,92	6,90	0,0083	0,0068
ASAPSO-ENN [17]	0,91	7,58	0,0087	0,0070
APSO-ENN [17]	0,88	8,82	0,0094	0,0073
PSO-ENN [17]	0,86	9,96	0,0100	0,0078
ENN [17]	0,84	1,18	0,0109	0,0084

As indicated in the performance table 2 and figure 13, the FEM+SRVM model offers the best model in predicting the dam vibration compaction with RMSE (0,0083), and MAE (0,0068) in figure 12 (a), and R^2 = 0,92, the best MSE (6,90) in figure 12 (b). ASAPSO-ENN has slightly lower (0,91, 7,58, 0,0087, 0,0070) and PSO-ENN (0,86; 9,96; 0,0100; 0,0078), respectively. The lowest accuracy is found in the baseline ENN (0,84, 1,18, 0,0109, 0,0084). These findings affirm that the incorporation of numerical simulation based on FEM and the use of ML based on SRVM prediction constitute an excellent method of enhancing the accuracy of estimating the quality of compaction and optimization of dam vibration compaction parameters.

The depth in the dam vibration compaction test provides the degree of the soil layer level to measure the depth of penetration of compaction energy. The speed of the roller determines the energy transfer to the soil, and the vibration frequency determines the dynamic stress to achieve maximum particle rearrangement. The height of each layer that has been compacted depends on lift thickness, and this influences efficiency. Soil density (ρ) is a measure of the achieved densification, and the relative compaction (%), in comparison between the achieved and the maximum density, is used to select the best parameters with the proposed FEM+SRVM.



(a) (b)

Figure 13. Comparative evaluation shows the proposed FEM-SRVM model achieving (a) RMSE and MSE, (B) R^2, and MAE

Table 3. FEM simulation results showing stress, deformation, and soil densification under varying compaction parameters

Depth (cm)	Roller Speed (m/min)	Vibration Frequency (Hz)	Lift Thickness (cm)	Soil Density ρ (g/cc)	Relative Compaction (%)
10	1,5	30	30	1,92	98
20	1,5	30	30	1,90	97
30	1,5	30	30	1,88	95
40	1,5	30	30	1,85	93
50	1,5	30	30	1,82	91

Table 3 depicts the FEM-based simulation of densification of soils at different depths under a constant roller speed (1,5¯ m/min), vibration frequency (30¯Hz), and lift thickness (30 cm) at a depth of 10cm. The density of the soil declines slowly as the depth of the soil increases to 1,82 g/cc at a depth of 50 cm, and relative compaction to 91 percent. Such findings prove that the model can predict depth-dependent compaction. Combined with the suggested FEM+SRVM, it allows for predicting and optimizing roller parameters precisely, and the results would be dam vibration compaction, which is efficient and does not require a lot of field testing.

To investigate the contribution of each component in the proposed FEM+SRVM framework, an ablation study was conducted by systematically removing or modifying key elements of the model, including the FEM simulation features, the SSVM module, and the Random Forest (RF) validation. The performance was evaluated using the metrics R^2, MSE, RMSE, and MAE on the same test dataset of the Dam Vibration Compaction Dataset.

Table 4. Impact of Model Components on FEM+SRVM Performance

Model Variant	R^2	MSE	RMSE	MAE
FEM + SRVM [Proposed]	0,92	6,90	0,0083	0,0068
SRVM without FEM Features	0,87	9,45	0,0097	0,0076
SSVM Only	0,89	8,32	0,0091	0,0072
RF Only	0,85	10,12	0,0101	0,0080
FEM Only	0,78	12,45	0,0112	0,0090

The study evaluates the FEM+SRVM framework through an ablation analysis (table 4) on the Dam Vibration Compaction Dataset, assessing the impact of various components like FEM simulation features, the SSVM module, and Random Forest validation. Results indicate that the full FEM+SRVM model achieves the best accuracy (R^2 = 0,92) and lowest error metrics (MSE: 6,90, RMSE: 0,0083, MAE: 0,0068). Removing FEM features or relying on individual components led to reduced performance, underscoring the importance of their integration.

DISCUSSION

This research integrates the finite element method with a scalable random vector machine framework to optimize vibration compaction in dam construction. Beyond improved machine learning performance, the results provide meaningful geotechnical insights.

The optimal vibration frequency of 30 Hz can be linked to the natural frequency of the tested soil layer and thickness, enabling efficient energy transfer and enhanced densification. Frequencies outside this range resulted in reduced compaction efficiency, consistent with soil dynamics principles. The simulated stress distribution patterns (figure 11a) exhibit trends aligned with Boussinesq theory for elastic half-spaces, while localized densification reflects granular media behavior, confirming the physical validity of the numerical model.

While ASAPSO-ENN(17) obtained an R^2 of 0,91, the FEM+SRVM model achieves 0,92, indicating a small but meaningful improvement that also integrates geotechnical reasoning. Compared to GBDT(15) (RMSE <0,041) and IFO-RF(16) (MSE = 0,0000602), the FEM+SRVM model provides competitive predictive accuracy while explicitly simulating soil stress responses. This shows that the marginal improvement is justified not only statistically but also in terms of physical interpretability.

Despite overall high accuracy, relative compaction decreases to 91 % at a depth of 50 cm, indicating a limitation in the effective compaction depth for the chosen optimal parameters. This drop highlights the importance of accounting for soil heterogeneity, boundary effects, and layer-specific behavior. Some dispersion is also observed in stress simulations due to local soil property variations, emphasizing the need for site-specific adjustments when applying the model in practice.

Traditional models such as ENN and its PSO/ASAPSO variants face difficulties handling high-dimensional, nonlinear soil-vibration interactions. PSO-ENN may converge slowly on larger datasets and become trapped in local optima. While ASAPSO-ENN improves convergence, it still cannot fully model dynamic soil responses and carries computational complexity that limits its generalization across varying field conditions.

The challenges identified in the Introduction are directly addressed by the proposed framework. The difficulty in predicting internal soil behavior is mitigated through FEM-based stress and densification simulations. Parameter optimization is achieved by coupling these simulations with the SRVM predictor, which identifies effective vibration frequencies and operating conditions. Modeling of heterogeneous soil mixtures is partially achieved through layered FEM representation, while the observed reduction in compaction at greater depths highlights the current limitations of the approach.

While the FEM+SRVM model shows high accuracy, limitations include reduced compaction beyond 40-50 cm, soil heterogeneity affecting reliability, and FEM simplifications that may not capture complex stress patterns. Future work should validate the model on independent sites, improve computational efficiency, and extend its applicability to heterogeneous soils and extreme conditions, directly addressing the limitations identified in this study.

CONCLUSION

The research illustrates that a combination of the FEM simulation with an ML-based SRVM is an effective model in the analysis and optimization of vibration compaction during earth-rock dam construction. The FEM model is used to predict the internal stress distribution and soil densification in a precise way using the Dam Vibration Compaction Dataset, with 25 features (field, laboratory, machine, and simulation sources), and the SRVM algorithm provides high precision in the accuracy of prediction of the quality of compaction. The integrated method results in vibration frequency as the most important parameter and a low MAE of 0,0068, R^2 = 0,92, and Relative Compaction (98 %) at the 10 cm depth, which proves the reliability of the model. This methodology lessens the aspect of trial and error, builds efficiency, and guarantees better soil density, mechanical stability, and long-term dam performance. The quality of the data set of the models and FEM assumptions is important in model performance, and extreme environmental conditions and non-homogeneous soils can lower the reliability of the predictions. The adaptive ML models, real-time monitoring, and integration with IoT sensors can be considered in the future to streamline the process of dam compaction.

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