Modelling Plate Penetration in Bekker Soil Model Using Machine Learning for Off-Road Vehicles

A. Nazari Chamki[1], A. Mardani[1*], A. Hosainpour[1]

1- Department of Mechanical Engineering of Biosystems, Faculty of Agriculture, Urmia University, Urmia, Iran
(*- Corresponding Author Email: a.mardani@urmia.ac.ir)
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Abstract

The study of soil behaviour in wheel interaction is complex due to the wheel's geometry and the varying soil conditions. Traditional measurements of soil parameters, such as the Bevameter and the cone penetrometer, are time-consuming and labour-intensive. This research presents a machine learning-based approach to predict soil sinkage in plate penetration tests, providing a suitable alternative to conventional methods. A soil bin with controlled experimental conditions was used to collect data, which was measured by a load cell and a magnetic encoder at a constant penetration rate of 4 mm s^{-1}. Two main machine learning models were selected; XGBoost and CatBoost. Hybrid versions of these models were developed using the Shrike Bird Optimisation Algorithm (SBOA). The results showed that the hybrid models outperformed the base models. The SBOA-CatBoost hybrid model achieved the highest accuracy on the training data with a coefficient of determination of 0.99, a mean square error of 2.81, and a mean absolute error of 0.79. The findings of this study highlight the potential of machine learning as a cost-effective and efficient alternative to traditional methods for measuring soil parameters. Further research is recommended to validate these models in different soil types and conditions.

Keywords: Bevameter, CatBoost, SBOA, Soil bin, Terramechanics, XGBoost

Introduction

The study of soil behaviour during interaction with off-road vehicles is a complex process. Several factors, including soil type, wheel geometry, and soil density, significantly influence the behaviour of the soil (Laughery, Gerhart, & Muench, 2000). The most important methods and equipment for measuring soil properties are the cone penetrometer and the Bevameter (Kim, Im, Choi, Oh, & Park, 2021; Taghavifar & Mardani, 2014a; Van, Matsuo, Koumoto, & Inaba, 2008). The Bevameter measures multiple soil quantities for numerical and analytical soil simulations to predict the traction device's interaction with soil (Mason *et al.*, 2020). The Bevameter is the standard method for scientific exploration, soil engineering, and off-road vehicle design (De Janosi, 1959). On the other hand, the Bevameter technique provides the closest simulation of vehicle loading conditions among the various measurement techniques currently used (Wong, 1989).

Among the soil parameters, soil resistance to penetration and shear stress are factors that affect the machine's ability to move, limiting both the terrain's potential and traction (Taghavifar & Mardani, 2017). The soil deformation parameters in the Bekker equation (k_c, k_φ, and n) are usually determined by several penetration plate tests of different sizes (b_1, b_2, and b_3), which define the pressure-sinkage relationship (Eq. 1). Normal loads are repeated with a set of penetration plate tests (rectangular or circular plate sizes) from 9.52 to 76.2 mm in width or diameter (Bekker, 1969).

$$P = (\frac{k_c}{b} + k_\varphi)Z^n \tag{1}$$

where P is the pressure on the plates, b is the plate's diameter, and Z is the soil sinkage.

Measuring soil parameters in both outdoor and indoor conditions presents several challenges, including the influence of environmental factors, sampling errors, and the associated costs and time requirements (Mardani & Golanbari, 2024). Predicting soil parameters for soil-vehicle interaction studies is essential in various aspects, including agriculture, industry, and the military. To model soil-wheel interaction, it is necessary to measure soil parameters such as soil resistance and soil hardness, which affect the amount of wheel sinkage and the traction force (Golanbari, Mardani, Hosainpour, & Taghavifar, 2023; Golanbari & Mardani, 2023). On the other hand, predicting soil parameters can be crucial in terms of cost and time. Additionally, utilising these parameters is crucial for optimising vehicle performance in agriculture, transportation, and off-road applications.

Mathematical, experimental, and numerical models have been widely used to predict soil parameters and tyre-soil interaction under different conditions (Brunskill *et al.*, 2011; Carman, 2002; Chou, Zhu, Skelton, Wagner, & Yang, 2011; Golanbari & Mardani, 2024). These models are developed based on pressure-sinkage and rolling resistance equations and mainly depend on laboratory and field data. However, mathematical models cannot accurately represent the actual conditions of wheel-soil interaction and often exhibit significant errors due to oversimplification and insufficient accuracy in modelling the soil's nonlinear behaviour (Golanbari, Mardani, Hosainpour, & Taghavifar, 2025). In recent years, the use of machine learning models has been introduced in various fields of Terramechanical studies (Golanbari *et al.*, 2023; Golanbari, Mardani, Farhadi, & Nazari Chamki, 2025; Huang, Zhang, & Xie, 2022; Taghavifar & Mardani, 2014b; Taghavifar, Mardani, & Karim-Maslak, 2014). These methods have become a suitable alternative to traditional mathematical and semi-empirical methods due to their ability to model nonlinear and complex relationships between input and output variables (Golanbari, Mardani, Farhadi, & Reina, 2024).

In a study by Rashidi and Gholami (2010), the finite element method (FEM) was used to predict soil sinkage under multiple loads. The study showed that FEM can more accurately model the soil behaviour under repeated loads. The results of this study showed that the first three loads have the most significant impact on soil sinkage, accounting for approximately 89% of the total soil sinkage. These findings underscore the significance of employing numerical methods in predicting soil behaviour under off-road vehicle loads.

Thornton, Pesheck, and Jayakumar (2023) have introduced a new method that predicts the results of the Bevameter using a reduced model (ROM). This method is integrated into a multi-objective optimisation framework for optimising the properties of the discrete element method (DEM). Negrut, Hu, Li, Unjhawala, and Serban (2023) developed the concept of virtual Bevameter tests using computer simulations. This method uses a continuous representation model to generate accurate data for calibrating soil contact models and has been proposed as an alternative to traditional Bevameter tests. In a study by Golanbari *et al.* (2023), a deep neural network (DNN) was used to investigate the plate penetration rate in determining soil parameters using soil pressure-sinkage diagrams. By varying the plate penetration rate, they demonstrated that different parameters could be obtained for the same soil type under the same initial conditions.

According to previous studies, most research has been conducted using traditional methods. In contrast, few studies have employed artificial intelligence-based models to enhance the accuracy of predicting soil parameters and their behaviour under various conditions. However, among the studies based on machine learning methods, there have been limited studies conducted to predict soil response based on multifactorial inputs without simplifying the influential variables. This study aims to develop a data-driven model to predict soil behaviour under off-road vehicle loading conditions using the results of plate penetration tests conducted in a laboratory environment. Unlike conventional approaches, the proposed framework preserves the complexity of the experimental variables and utilises modern machine learning techniques, including CatBoost and XGBoost, to enhance prediction accuracy. Additionally, the Shrike Bird Optimisation Algorithm (SBOA), a meta-heuristic, is employed to optimise the hyperparameters of machine learning models. This combined strategy—employed for the first time in the field of Terramechanics—demonstrates suitable predictive performance and model robustness when tested on a fully independent experimental dataset, thereby highlighting its potential for broader applications in soils.

Materials and Methods

A soil bin is a laboratory environment that allows for the precise control of experimental factors used to study the interaction between a machine and soil. A soil bin usually consists of a soil channel with specific dimensions, a carrier, a power transmission system, and measurement equipment. The soil bin used in this study is a fixed metal structure located on the ground surface, and the soil bed is wholly separated from the ground. The soil bin consists of a 24 m long soil channel, a 2 m wide channel, and a 1 m deep soil layer. Fig. 1 shows the various components of a soil bin.

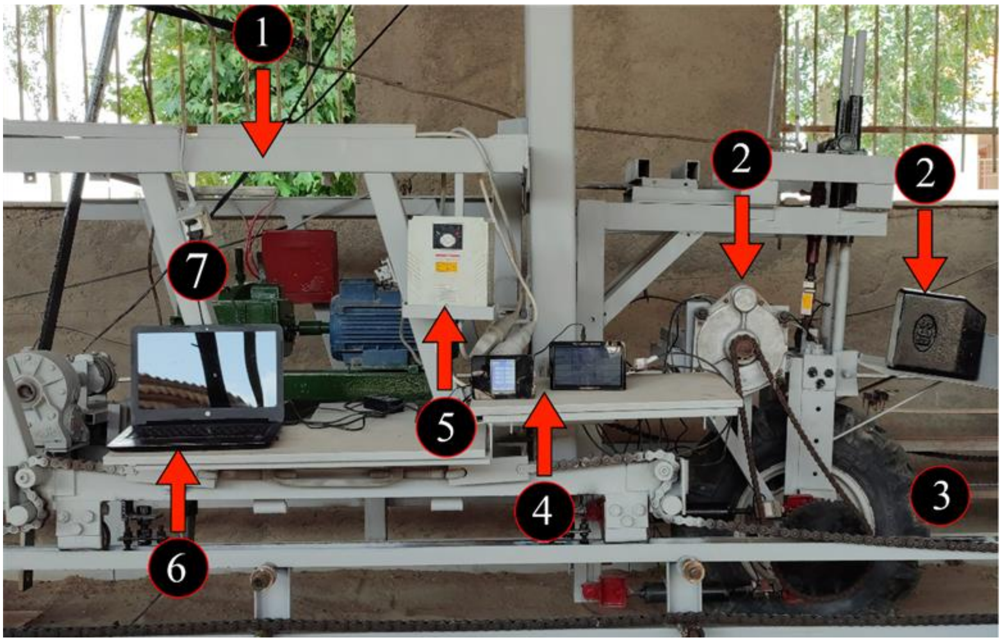

Fig. 1. Soil bin and its components: 1- Chassis, 2- Dead load location, 3- Traction device (wheel), 4- Data logger, 5- Inverter, 6- Computer, and 7- Bevameter

The linear speed of the pneumatic wheel or track wheel is equivalent to the carrier's forward speed. A three-phase industrial electric motor with a power of 22 kW (30 hp) was used to provide the required power for the carrier. This electric motor provides the driving force required to move the carrier, which is transmitted through the gear to the axle at the edge of the channel.

Considering that the forward speed of the wheel is one of the dynamic parameters studied in this research, an inverter manufactured by the LS brand (SV 220 IS5-2NO, 380V, South Korea) was used to control the rotational speed of the drive motor. This ultimately leads to the linear speed of the driven carrier. In this study, different forward speeds were used for the movement of the carrier, including speeds of 1, 2, and 3 km h^{-1}.

Considering the motor's rated speed of 1457 rpm, the inverter can apply a speed from zero to about 21 km h^{-1}, which can be controlled precisely. The forward speed has a linear relationship with the inverter's frequency, which is shown in Fig. 2 as a calibration chart for obtaining different speeds.

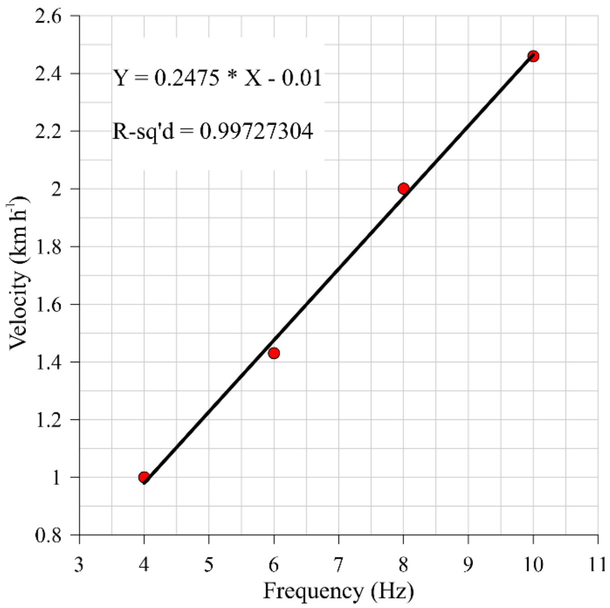

Fig. 2. Inverter calibration diagram and its relationship with carrier forward speed

Furthermore, three vertical load levels of 2, 3, and 4 kN were applied as dead loads on the wheel to consider the effect of vertical load on soil parameters. For this purpose, the dead load was placed on the carrier at predetermined locations in each stage of the tests. The location of the load was designed to apply it thoroughly and balance it without creating lateral forces on the wheel. On the other hand, the number of passes was considered another parameter. Since previous research has shown that the most significant changes in soil texture and density occur during the initial passes, seven pass levels, including passes 1, 2, 3, 5, 7, 10, and 15, were considered for this study. Also, the type of traction device can affect the soil differently due to variations in geometry and contact surface, which alter the stress and load distribution on the soil (Ani *et al.*, 2018). Therefore, two conventional traction factors, including pneumatic wheels and track wheels, were considered in this study. Table 1 shows the experimental parameters and their descriptive statistics. These parameters were used as inputs to the machine learning models.

Table 1- Descriptive statistics of training data

Parameters	Mean	Std Dev	Min	Max	Skewness	Kurtosis
Traction Device	1.474	0.4993	1⁕	2⁕	0.103363	-1.9896
Vertical load (kN)	3.492	0.770	2	4	-1.10244	-0.4277
Forward speed (km h^{-1})	2.028	0.8056	1	3	-0.04987	-1.4574
Multiple pass	5.763	4.8439	1	15	0.886232	-0.6568
Plate diameter (mm)	64	15	50	80	0.073635	-1.9948
Pressure (kPa)	156.9	110.01	0	565	0.495656	-0.2336

⁕Note: Values ‘1’ and ‘2’ under the “Traction Device Type” column represent categorical codes for the two traction systems used: 1 = pneumatic tire, and 2 = track.

Table 1 presents the distribution characteristics of the experimental data. The means indicate the centrality of the data, and the standard deviation indicates the degree of dispersion of the data around the mean. The minimum and maximum values indicate the range of the parameters. The skewness index describes the shape of the data distribution, with positive values indicating a longer tail to the right of the normal distribution and negative values indicating a longer tail to the left of the normal distribution. The kurtosis value indicates the degree of concentration of the data around the mean, with negative values indicating a flatter distribution and positive values indicating a more peaked distribution. The parameters of the traction device type and the test plate's diameter show an almost symmetrical distribution with negative skewness, indicating that the data are concentrated around the middle values.

In contrast, the parameter of the number of passes with positive skewness exhibits an asymmetrical distribution, with the data concentrated at lower values. The selection of more test levels in the initial traffic can justify this. The vertical load and forward speed have symmetrical distributions. Vertical pressure also has a relatively balanced distribution with a slight tendency toward lower values.

The channel was filled with clay loam soil that had been sieved through a 50 mm sieve. This soil was randomly selected and collected from a single location in the region's agricultural soils. A 50 mm sieve was used to remove stones and large clods. This procedure ensured that the soil was approximately homogeneous throughout the soil channel, thereby preventing measurement errors caused by large particles. Table 2 shows the characteristics of the soil used.

Table 2- Characteristics of the soil bin soil

Parameter	Value
Sand	35%
Silt	26%
Clay	39%
Moisture content	8%
Bulk density	1460 kg m^{-3}
Young's modulus	0.3 MPa
Poisson's ratio	0.29
Angle of internal friction	32

Data acquisition

A portable Bevameter is mounted on the carrier. It can be used to measure the triple parameters of the Bekker equation of the soil immediately after the wheel passes. Fig. 3 schematically shows the different components of the Bevameter.

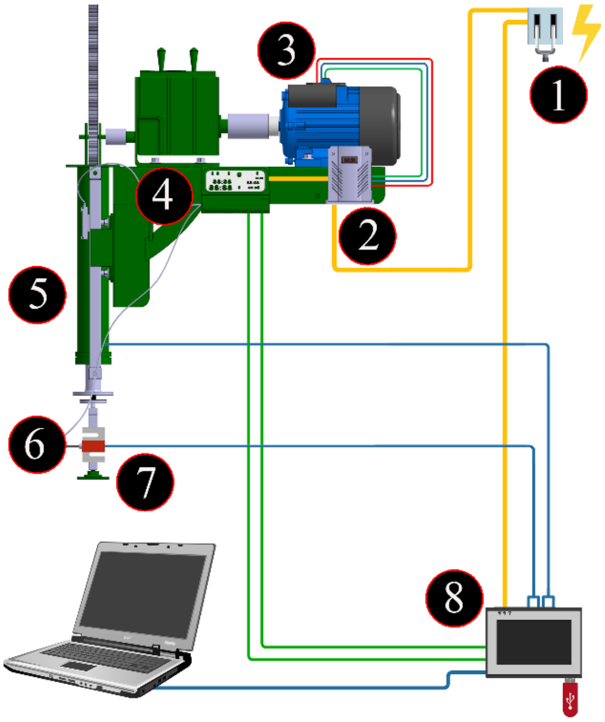

Fig. 3. Schematic of the Bevameter and its attachments: 1- Power supply, 2- Inverter, 3- Electric motor, 4- Bevameter, 5- linear magnetic encoder, 6- S-shaped load cell, 7- Infiltration plates, 8- Data logger

The Bevameter operates by measuring two parameters. One is the vertical force applied to the plates, which is measured by S-type load cells. The other is the linear movement of the plates, which is measured by a linear magnetic encoder. In this study, two circular plates with diameters of 50 and 80 mm were used.

After installing the plates on the Bevameter, the plates penetrated the soil at a constant speed of 4 mm s^{-1} to a depth of 70 mm. A load cell and a magnetic encoder measure the vertical force required for penetration and the penetration depth, respectively. The measurements should be such that each load cell's data corresponds to the magnetic encoder data. On the other hand, to perform statistical analyses and examine the effect of variables on the experimental results, the measured data in each experiment should be stored in a non-volatile memory. The digital data logger can connect 10 parallel channels for different sensors and provide cumulative output. This ensures that the corresponding data from the load cell and magnetic encoder are accurately recorded at a given time. This system is capable of recording data at a frequency of 60 Hz.

Due to the constant speed, the amount of data in each experimental treatment was almost equal. However, there were some differences, so using a program written in Python 3.10, the number of experimental data points for all treatments was equalised without changing the trend. After removing noise and pre-processing, a total of 15,620 data points remained and were used for model training and validation. Additionally, an independent experimental trial was conducted using a combination of vertical load, forward speed, and the number of passes, which were not included in the training dataset. From this trial, 100 data points were selected as an entirely separate test set to evaluate the model's generalisation ability. Of the 15,620 training data points, 80% were used for training, and 20% were used for validation.

In this study, to reduce the sensitivity of machine learning models to the scale of the input data, the data were normalised using the Standardisation method. This method is one of the most common normalisation methods in data pre-processing. Data normalisation aims to convert the data into values with a mean of zero and a standard deviation of one. This ensures that the data is on the same scale and enables machine learning algorithms to perform more effectively. Standardisation is performed according to Eq. 2.

$$z_{ij} = \frac{x_{ij} - \mu_{ij}}{\sigma_{ij}} \qquad (2)$$

where x_{ij} is the value of the i-th sample in the j-th feature, μ_{ij} is the mean of the jth feature, and σ_{ij} is the standard deviation of the jth feature.

Machine learning methods representation

This section introduces machine learning models for predicting soil sinkage in the Bekker method based on the independent variables used in this research. Machine learning models, including XGBoost and CatBoost as basic models, as well as hybrid versions of these models optimised with the SBOA algorithm, are examined. The SBOA algorithm is used to fine-tune each model by minimising the root mean square error (RMSE) on the validation data through iterative optimisation. A summary of the hyperparameters subjected to optimisation, along with their respective types and ranges, is presented in Table 3. In addition, details of the data preparation process and model evaluation metrics are also provided in this section.

Table 3- Optimised hyperparameters and their value ranges for XGBoost and CatBoost models using the SBOA algorithm

XGBoost		CatBoost	
Hyperparameter	**Range**	**Hyperparameter**	**Range**
“n”_estimators	100 – 1000	Iterations	100 – 1000
Max_depth	3 – 10	Depth	3 – 10
Learning_rate	0.01 – 0.3	Learning_rate	0.01 – 0.3
Reg_lambda	1 – 10	L2_leaf_reg	1 – 10
Reg_alpha	0 – 10	Subsample	0.5 – 1
Subsample	0.5 – 1	Colsample_bylevel	0.5 – 1
Colsample_bytree	0.5 – 1	Min_data_in_leaf	1 – 10
Colsample_bylevel	0.5 – 1	Border_count	1 – 255
Min_child_weight	1 – 10	Random_strength	0 – 10
Gamma	0 – 1	Bagging_temperature	0 – 1
Scale_pos_weight	0 – 1	Od_type	Iter / IncToDec
Max_delta_step	0 – 1	Early_stopping_rounds	10 – 250

The selection of XGBoost and CatBoost models as the base models is due to their better performance in previous studies compared to other boosting-based methods (Bentéjac, Csörgő, & Martínez-Muñoz, 2021; Golanbari *et al.*, 2025). These models were selected as suitable bases for this research due to their ability to handle complex data, deal with nonlinear features, and reduce the problem of overfitting. On the other hand, hybrid models of SBOA-XGBoost and SBOA-CatBoost were utilised to enhance the performance of the basic models and optimise the model hyperparameters. The SBOA algorithm was chosen because it performed better than other optimisation algorithms, such as the GWA and PSO, which were used as efficient optimisation methods in the study to adjust the hyperparameters of similar models (Golanbari *et al.*, 2025).

XGBoost is a gradient-boosting method that has been extended to optimise decision tree models using additive trees. This method's advantages include avoiding overfitting using pruning, regularisation, and parallel computing. CatBoost is an optimised version of the gradient boosting algorithm specifically developed for data with categorical features. It also supports GPU processing and reduces the effect of overfitting. This study uses XGBoost and CATBoost without optimisation to compare the initial model performance.

Hybrid models of the base models were developed to enhance their performance, utilising the SBOA algorithm to fine-tune the hyperparameters of the models. SBOA is a new meta-heuristic optimisation algorithm inspired by the hunting behaviour of the shrike bird. This algorithm has two main stages for optimisation: Exploration and Exploitation. In the Exploration stage, the shrike bird first searches a large area for potential prey (different solutions). This stage is equivalent to random sampling in the search space. In the local optimisation stage (Exploitation), the algorithm selects and improves the best solution after finding suitable positions. In this research, this stage involves adjusting the optimal values of hyperparameters in machine learning models. These two models are optimised versions, and their performances are compared to that of the base models. The hyperparameters selected for optimisation were to avoid excessive model complexity, prevent overfitting, and increase model accuracy and convergence.

Six evaluation metrics, including coefficient of determination (R^2), mean square error (MSE), root mean square error (RMSE), mean absolute error (MAE), maximum Error, and symmetric mean absolute percentage error (SMAPE), were used to measure the accuracy of the predictions. The calculations for these metrics are shown in Equations 3 to 8.

$$R^2 = \frac{\sum (Y_i - \hat{Y}_i)^2}{\sum (Y_i - \bar{Y})^2} \quad (3)$$

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(Y_i - \hat{Y}_i)^2 \quad (4)$$

$$MAE = \frac{1}{n}\sum_{i=1}^{n}\left|Y_i - \hat{Y}_i\right| \quad (5)$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(Y_i - \hat{Y}_i)^2} \quad (6)$$

$$Max\,Error = \max_{i=1}^{n}(Y_i - \hat{Y}_i) \quad (7)$$

$$Symmetric\,MAPE = \frac{1}{n}\sum_{i=1}^{n}\frac{\left|Y_i - \hat{Y}_i\right|}{\left|Y\right| + \left|\hat{Y}_i\right|} \quad (8)$$

Result and Discussion

In this study, the sinkage value in pressure-sinkage tests under the influence of six parameters was predicted using machine learning methods. The results of the first part of this study are a sensitivity analysis examining the effect of changes in input parameters on model predictions. The sensitivity and Probability-based Hybrid Analysis (SPHA) method is used to systematically evaluate the effect of input parameters on the model output. By assigning probability distributions to each parameter and performing systematic sampling, SPHA simultaneously calculates both first-order sensitivity indices, which represent the independent contribution of each parameter, and overall sensitivity indices that account for interactive and nonlinear effects. Fig. 4 shows the sensitivity analysis graph of parameters on the sinkage output.

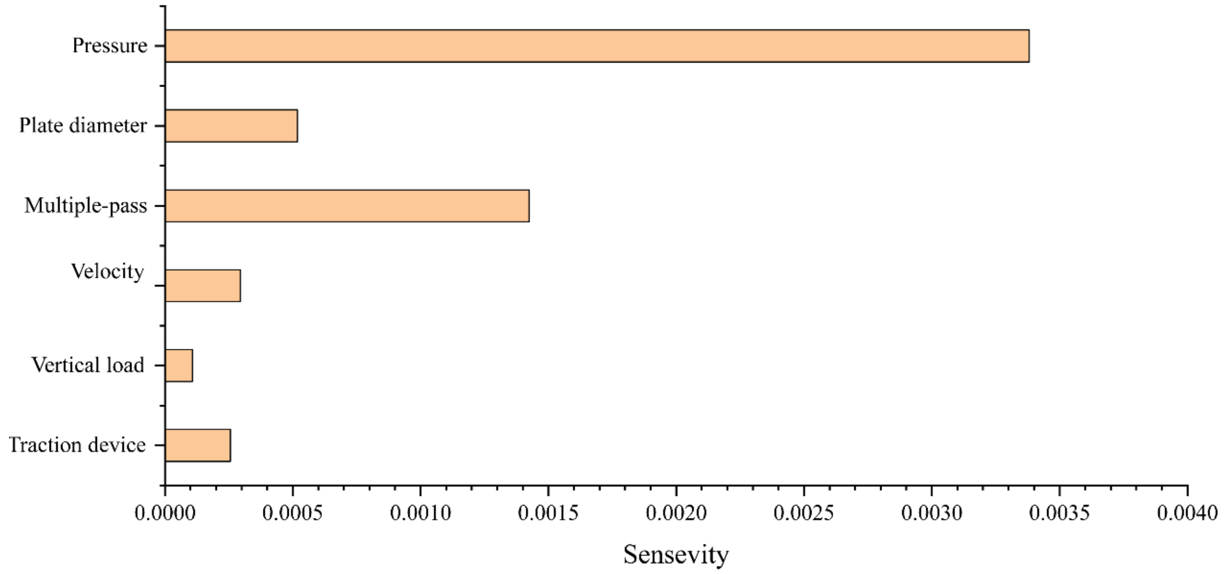

Fig. 4. Sensitivity analysis chart

The diagram in Fig. 4 shows that the most influential variable in the model is the pressure on the plates. The number of passes variable is also of considerable importance. The plate's diameter is also of third importance. The subsequent influential factors are forward speed, type of traction agent, and vertical load on the wheel, respectively.

Machine Learning models Performance

This study evaluated the performance of several machine learning models, including CATBoost, XGBoost, SBOA-CATBoost, and SBOA-XGBoost hybrid models for sinkage prediction. After training, metrics for the models were calculated based on the difference between the predicted and actual values. Table 4 compares the performance of the models with the training data.

Table 4- Performance of machine learning models

Model	MSE	RMSE	MAE	S-MAPE	R^2
SBOA-CATBoost	2.81	1.67	0.79	9.26	0.99
SBOA-XGBoost	2.77	1.66	0.80	9.48	0.99
CATBoost Base	14.89	3.86	2.61	22.6	0.95
XGBoost Base	31.16	5.58	3.90	28.1	0.89

Comparing the performance of CATBoost and XGBoost models in two base model and optimised with the SBOA algorithm on the training data show that the evaluation criteria on the optimised models have improved.

A comparison of the MSE, RMSE, MAE, and S-MAPE criteria reveals that the hybrid models outperform the basic models, indicating a better fit with the experimental data. However, in studies between the vehicle and the soil, due to the high complexity of the interactions and the large number of influential parameters, the performance of all models can be considered appropriate compared to conventional methods.

On the other hand, comparing the two hybrid models reveals that their performance is remarkably similar. SBOA-XGBoost performs slightly better in the MSE and RMSE criteria, while SBOA-CATBoost performs more appropriately in the MAE and SMAPE criteria. These results show that the SBOA algorithm has significantly improved the performance of the models.

Since the performance of the models on the training metrics is very close, the performance of the models on unseen test data is significant for the final selection between the two optimised models, thereby achieving the stability and generalisability of the models. Therefore, the developed machine learning models were evaluated on new and unseen data. Despite the favourable performance of the models on the training data, the primary test for selecting a suitable model for sinkage prediction is the model performance under actual conditions.

In this section, we will analyse the prediction results of the test data. Fig. 5 shows the regression plots of the models on unseen data, along with the experimental data. This plot compares the fit of the predicted values with the experimental values, using the R^2 metric.

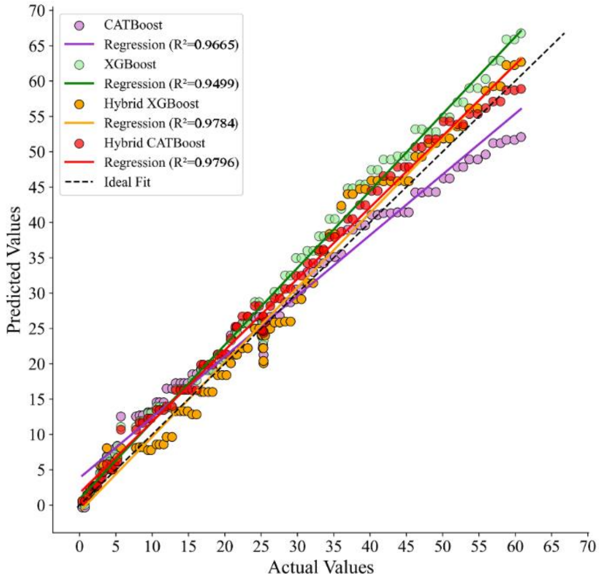

Fig. 5. Regression diagram of machine learning models

The graph in Fig. 5 shows that hybrid models with higher R^2 values perform better than the base models, indicating the positive effect of the hybridisation technique on model optimisation with the algorithm. The prediction points of hybrid models, especially Hybrid CATBoost, are closer to the Ideal Fit line, whereas pure XGBoost exhibits more dispersion in its extreme values. These results demonstrate that hybrid models are more stable in the face of actual data and yield better predictions. In general, when comparing the regression graphs, the Hybrid CATBoost model performed best.

The residuals graph illustrates the difference between the predicted values and the actual values in both quantitative and qualitative terms. Fig. 6 presents the analysis of the residual graphs of the four models: CATBoost, XGBoost, Hybrid XGBoost, and Hybrid CATBoost.

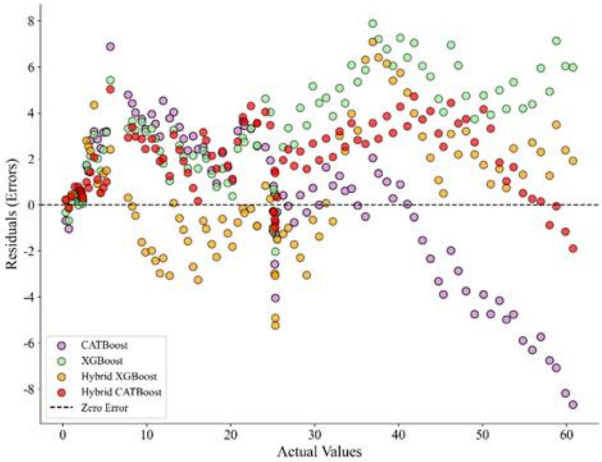

Fig. 6. Residuals plot analysis for machine learning models

Analysis of the residual plots shows that the hybrid models have errors closer to the zero line and less dispersion than the basic CATBoost and XGBoost models. The SBOA-CATBoost model has the lowest error rate and the most stable performance. However, errors above zero in most data ranges indicate that the model overpredicts slightly more than the actual values. In contrast, XGBoost has the highest errors and dispersion.

Metrics including MSE, RMSE, MAE, Max Error, and SMAPE were also used to evaluate the models utilising the unseen data. Fig. 7 shows the evaluation metrics graph for each model.

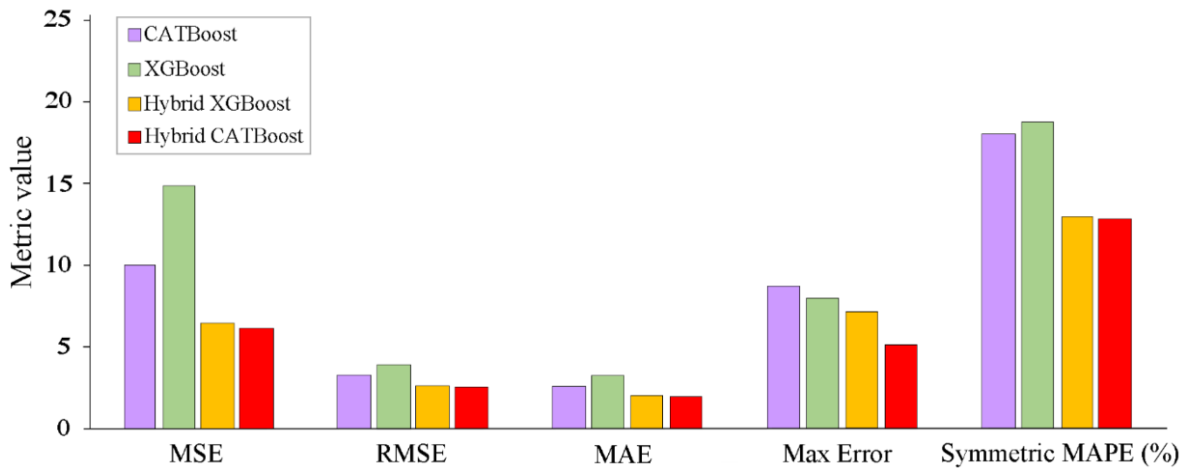

Fig. 7. Graph of model metrics on unseen data

The comparison chart of the evaluation criteria shows that the CATBoost hybrid model performed better than the others in all criteria (MSE, RMSE, MAE, Max Error, and SMAPE). Although the difference between the CATBoost hybrid model and the XGBoost hybrid model is minor, both models performed well. However, the basic XGBoost model has the lowest values in all criteria, indicating its high accuracy and low prediction error. In contrast, the basic XGBoost has reached the highest error values in all criteria except for the maximum error, indicating its weakness in prediction compared to other models. However, it can still provide acceptable prediction accuracy. The hybrid models have performed better, especially in terms of MSE and SMAPE, which indicates the optimisation algorithm's ability to reduce significant errors. These results confirm the superiority of hybridisation techniques in improving the performance of models.

Taylor plot was also used to evaluate the forecasting models in this study. This plot facilitates the comparison of model performance by combining three metrics: correlation coefficient, normalised standard deviation, and normalised RMSE. In this plot, the reference curve represents the actual data, and models closer to this curve have a higher correlation, a more appropriate standard deviation, and lower error. Fig. 8 shows the Taylor plot of the models.

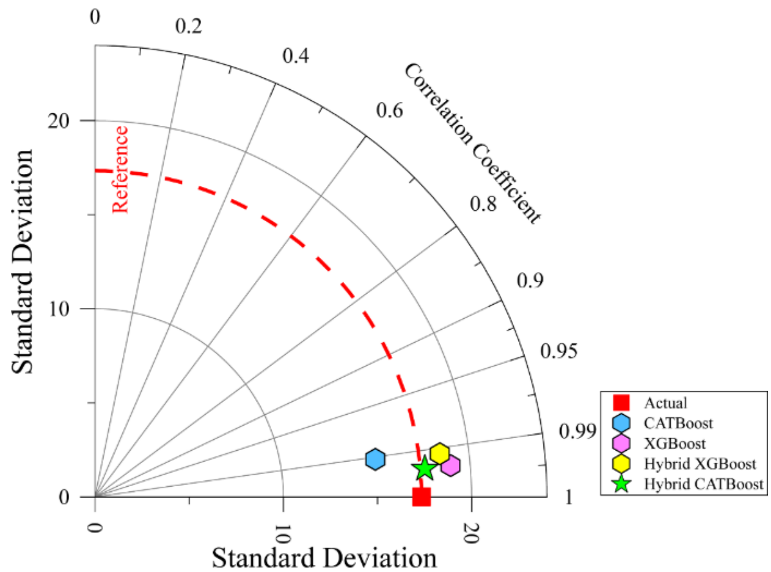

Fig. 8. Taylor diagram for the performance of machine learning models

The Taylor diagram indicates that the Hybrid CATBoost model performed best, with the highest correlation, an ideal normalised standard deviation, and the lowest normalised error. The Hybrid XGBoost model performed worse than the Hybrid CATBoost model, but performed well overall. The hybrid models' good performance indicates the positive effect of hybridisation in improving both base models. In contrast, the base CATBoost model, although showing an acceptable correlation, exhibits a higher standard deviation, indicating that its predictions have more fluctuations than those of the hybrid models. The base XGBoost model, with the lowest correlation and the highest standard deviation, performed the worst among the models. These results underscore the need for hybrid approaches to strike a desired balance between accuracy, stability, and generalisability.

The graph in Fig. 9 shows the trend of changes in the actual syncing and predictions of four machine learning models on unseen data.

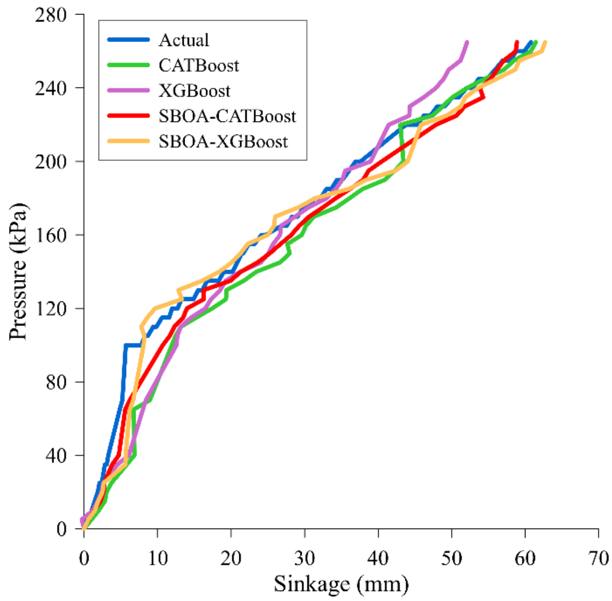

Fig. 9. The prediction trend of machine learning models compared to actual data

The analysis of sinkage trends indicates that all models can somewhat predict changes in sinkage with pressure variations. However, the hybrid models outperform the basic models. SBOA-CATBoost also has the most stable forecast trend in all pressure ranges. The basic models exhibit more fluctuations in their predictions, indicating the effect of SBOA optimisation in reducing the variance of the forecasts.

It can also be seen from the trend diagram that the SBOA-XGBoost model has followed the trend of the experimental data well, except in parts of the middle. However, its forecast fluctuation is greater than that of the CATBoost hybrid model. The basic CATBoost model has also recognised the trend well, but has more fluctuation than the two hybrid models. Additionally, despite minimal fluctuation in the forecast, the XGBoost model has predicted the trend with a greater distance from the experimental data and exhibits a more significant error than the other models, which confirms the results of the previous sections.

On the other hand, it can be observed that the models tend to predict values lower than the actual ones, and this trend is visible in all models except for a portion of the XGBoost model. This type of prediction can be attributed to the asymmetry in the training data related to traffic, as most of the data were from low-traffic ranges, where the soil is looser than in higher-traffic areas. In this case, the pressure-sinkage diagram has a lower slope. Therefore, the models tend to predict lower values than the actual ones, as they learn more from this data to predict higher traffic. The results of this study demonstrate that machine learning models achieve sufficient accuracy in predicting soil sinkage using a Bevameter, making these models a viable alternative to time-consuming and costly laboratory and field methods for predicting soil parameters, provided they are appropriately calibrated across different soils. In real-time applications, recognising the soil type can help the vehicle perform better by adjusting its characteristics.

Conclusion

The present study investigates the application of machine learning models to predict soil indentation from plate penetration tests performed using a Bevameter. This approach aims to overcome the limitations of conventional methods, which often involve time-intensive laboratory and field procedures. To optimise model performance, the Shrike Bird Optimisation Algorithm (SBOA) was integrated with CatBoost and XGBoost algorithms. This hybridisation enabled the improved prediction of nonlinear behaviour and complex interactions between the wheel and soil. While these hybrid models significantly enhance accuracy, robustness, and generalisability, they also introduce increased computational complexity and longer training times due to the additional optimisation steps. The results indicate that the optimised models exhibit superior performance compared to their standalone counterparts, particularly in terms of prediction accuracy, robustness, and generalisability.

Sensitivity analysis revealed that the vertical pressure on the plates, the number of passes, and the plate diameter were the most significant factors influencing the rut depth. Furthermore, comparative analysis of the models using unseen data showed the superior performance of the hybrid approaches over the baseline models. Among them, the SBOA-CATBoost model achieved the highest correlation, the lowest prediction error, and the most consistent outputs on unseen data. However, the present study had certain limitations. Although the models showed promising performance, the experimental set used for evaluation was relatively small, which may affect the robustness of the generalisation assessment. Furthermore, given the homogeneity of the dataset, which consisted solely of clay loam soil, the generalisability of the models to other soil types and environmental conditions still needs to be validated. In particular, the lack of environmental diversity (variations in soil moisture, temperature, and initial compaction state) limits the applicability of the results to real-world off-road scenarios where such factors play a critical role in soil response.

Future research could expand the dataset to include a broader range of soil compositions and environmental scenarios, apply more rigorous validation techniques, such as cross-validation, and explore alternative or hybrid optimisation algorithms to further improve prediction accuracy and model robustness. As machine learning models evolve, their integration with soil mechanics will undoubtedly open up new avenues for optimising vehicle performance and minimising environmental impacts in off-road applications. Moreover, since the current study did not involve real-time implementation on actual vehicles, future efforts should also aim to assess the computational efficiency and hardware requirements of the proposed models in operational environments. Such investigations will be essential for evaluating the feasibility of integrating these models into real-world off-road vehicle systems.

Authors Contribution

A. Nazari Chamki: Conceptualisation, Data acquisition, Data pre and post processing, Numerical/computer simulation, Review and editing services

A. Mardani: Supervision, Conceptualisation, Validation, Review and editing services

A. Hosainpour: Supervision, Technical advice, Validation, Review and editing services

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مدل‌سازی نفوذ صفحه در مدل خاک بکر با استفاده از یادگیری ماشین برای وسایل نقلیه خارج از جاده

اکبر نظری چمکی[۱]، عارف مردانی[۱*]، عادل حسین پور[۱]

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چکیده

مطالعه رفتار خاک در تعامل چرخ با خاک به دلیل هندسه چرخ و شرایط متغیر خاک پیچیده است. اندازه‌گیری‌های سنتی پارامترهای خاک، مانند بوامتر و نفوذسنج مخروطی، زمان‌بر و پرزحمت هستند. این تحقیق یک رویکرد مبتنی بر یادگیری ماشین برای پیش‌بینی فرونشست خاک در آزمایش‌های نفوذ صفحه ارائه می‌دهد و جایگزین مناسبی برای روش‌های مرسوم ارائه می‌دهد. از یک انباره خاک با شرایط آزمایشگاهی کنترل‌شده برای جمع‌آوری داده‌ها استفاده شد. مقدار نیرو در هر لحظه توسط یک حسگر اندازه‌گیری بار و میزان فرورفتگی توسط یک خط‌کش دیجیتال با سرعت نفوذ ثابت ۴ میلی‌متر بر ثانیه ثبت شد. دو مدل اصلی یادگیری ماشین، XGBoost و CatBoost، انتخاب شدند. نسخه‌های ترکیبی این مدل‌ها با استفاده از الگوریتم بهینه‌سازی پرنده شرایک (SBOA) توسعه داده شدند. نتایج نشان داد که مدل‌های ترکیبی از مدل‌های پایه بهتر عمل می‌کنند. مدل ترکیبی SBOA-CatBoost با ضریب تعیین ۰/۹۹، میانگین مربعات خطا ۲/۸۱ و میانگین مطلق خطا ۰/۷۹، بالاترین دقت را در داده‌های آموزشی به‌دست آورد. یافته‌های این مطالعه، پتانسیل یادگیری ماشین را به‌عنوان جایگزینی مقرون به‌صرفه و کارآمد برای روش‌های سنتی اندازه‌گیری پارامترهای خاک برجسته می‌کند. تحقیقات بیشتر برای اعتبارسنجی این مدل‌ها در انواع و شرایط مختلف خاک توصیه می‌شود.

واژه‌های کلیدی: الگوریتم بهینه‌سازی پرنده شرایک، بوامتر، ترامکانیک، مخزن خاک، CatBoost، GBoost

۱- گروه مهندسی مکانیک بیوسیستم، دانشکده کشاورزی، دانشگاه ارومیه، ارومیه، ایران
(*- نویسنده مسئول: Email: a.mardani@urmia.ac.ir)

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