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Modeling Soil Pressure-Sinkage Characteristic as Affected by Sinkage rate using Deep Learning Optimized by Grey Wolf Algorithm

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Abstract

Due to the numerous variables that may influence the soil-machine interaction systems, predicting the mechanical response of soil interacting with off-road traction equipment is challenging. In this study, deep neural networks (DNNs) are chosen as a potential solution for explaining the varying soil sinkage rates because of their ability to model complex, multivariate, and dynamic systems. Plate sinkage tests were carried out using a Bevameter in a fixed-type soil bin with a 24 m length, 2 m width, and 1 m depth. Experimental tests were conducted at three sinkage rates for two plate sizes, with a soil water content of 10%. The provided empirical data on the soil pressure-sinkage relationship served as the basis for an algorithm capable of discerning the soil-machine interaction. From the iterative process, it was determined that a DNN, specifically a feed-forward back-propagation DNN with three hidden layers, is the optimal choice. The optimized DNN architecture is structured as 3-8-15-10-1, as determined by the Grey Wolf Optimization algorithm. While the Bekker equation had traditionally been employed as a widely accepted method for predicting soil pressure-sinkage behavior, it typically disregarded the influence of sinkage velocity of the soil. However, the findings revealed the significant impact of sinkage velocity on the parameters governing the soil deformation response. The trained DNN successfully incorporated the sinkage velocity into its structure and provided accurate results with an MSE value of 0.0871.

Keywords: Bevameter, Deep neural network, Off-road vehicle, Soil bin, Terramechanics

Introduction

A Bevameter can be used for calculating soil parameters through pressure-sinkage relationships. The obtained pressure-sinkage models are used to analyze the soil interaction with the vehicle tires. In this method, the investigation and analysis of soil-tire interaction also requires the measurement of the mechanical parameters of soil. The traction force created by the driving wheel, as well as the soil compaction due to vehicle traffic, are the results of the interaction between soil and tire. Factors such as traction, performance prediction, design, and stability of off-road vehicles can be analyzed through pressure-sinkage models (He, Wu, Ma, Wang, & Li, 2019). Therefore, any improvement in soil-tire interaction has a direct effect on the performance of off-road vehicles and equipment and reduces fuel consumption.

The experimental method is one of the essential methods for soil behavior modeling. In this research, the soil resistance versus penetration depth is measured. Researchers are interested in using these equations because many of the wheel and soil parameters are not included which results in ease of measurement. To develop pressure-sinkage

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relationships of loading plates for homogeneous soil, Bekker presented Eq. 1 using the Bevameter device (Bekker, 1957).

$$P = \left(\frac{K_c}{b} + K_\varphi\right).Z^n \quad (1)$$

Where P is the vertical pressure (kPa), n is the deformation equation exponent, K_c is the modulus of cohesion of the deformed soil (kN/m^{n+1}), K_φ is the modulus of friction of the deformed soil (kN/m^{n+2}), Z is sinkage of the loading plate (cm), and b is the smallest dimension of the plate (m). To calculate the coefficients of Eq. 1 based on Bekker's method, two loading plates with different widths should be used to solve the equation.

One popular method for soft computing is an artificial neural network (ANN), which is composed of interconnected neurons following specific algorithms. These networks are inspired by the human brain's structure and functioning and are used for pattern recognition (Taghavifar & Mardani, 2014b). Neural networks encompass machine learning algorithms that classify input data and produce desired outputs. They have multiple applications including pattern recognition, data classification, prediction, modeling, control, and robotics (Haykin, 1999; Roul *et al.*, 2009). ANNs are utilized to facilitate solving complex problems in various scientific and engineering fields, mainly where conventional mathematical modeling is not successful (Taghavifar & Mardani, 2014a). Deep Neural Networks (DNNs) utilize deep architectures with multiple hidden layers and identify complex patterns and relationships in datasets. They are trained with experimental data and are then validated and tested using independent datasets. DNNs achieve high performance and accuracy by minimizing the mean square error. The iterative exploration process and backpropagation allow DNNs to establish the optimal input-output relationship. After training, the model can be extended with new input values to predict, simulate, and re-establish the identified conditions of the test method. Fernandes *et al.* (2020), conducted experiments to evaluate the accuracy of ANN models in estimating soil infiltration resistance with standardized moisture. Based on soil infiltration resistance measured in the field and on soil moisture, the models used were obtained by multiple linear and nonlinear regression and ANNs. Pham *et al.* (2019), proposed a hybrid machine learning approach called MLP-BBO to predict the stabilization coefficient of soft soil. This method was based on the multilayer perceptron (MLP) neural network and Biogeography Based Optimization (BBO). Roul *et al.* (2009), used the ANN model to predict the behavior of tillage tools in different operating conditions and soil. Zhang & Kushwaha, (1999) used the radial basis function (RBF) in the artificial neural networks to estimate the draft force of thin blades in soil under multiple input variables. Taghavifar *et al.* (2013), used a neural network to investigate the wheel's behavior with soil under the influence of movement speed, vertical load, and tire pressure. To improve tractor performance on silty clay loam soil, Pieczarka *et al.* (2018) investigated the effects of soil moisture, soil compaction, horizontal soil deformation, and vertical load on traction force using MLP and RBF neural networks. The most efficient model was the MLP neural network.

Bekker´s method is a standard method used by researchers to determine soil parameters on a large scale and is simple to calculate. However, it has some shortcomings in field tests. Although the penetration velocity of the plates in the soil affects the soil sinkage, its effect is not taken into account in Bekker's method and other methods that are developed based on it (Kruger, Els, & Hamersma, 2023). The purpose of this research is to model the pressure-sinkage relationship with deep artificial neural networks and to investigate the effect of sinkage rate (which is related to loading time and machine speed) on the soil parameters. Lastly, the results of the modeling are compared with the experimental results.

Materials and Methods

Data acquisition

The plate sinkage experiments were carried out using a Bevameter installed on the carrier unit of a soil bin in the Terramechanics laboratory of Urmia University, Iran. The soil bin is a fixed-linear type soil bin with a 24 m length, 2 m width, and 1 m depth soil channel and provides optimal conditions for conducting experiments by eliminating boundary effects (Gheshlaghi & Mardani, 2021). The Bevameter utilized in this research consists of mechanical, electrical, and electronic parts. The mechanical part includes the chassis, worm gearbox, Rack and pinion gear mechanism, shell, shaft, one-way jack, and plates, as shown in Fig. 1. The mechanical part of the device works in such a way that the rotational movement of the gearbox is converted into linear movement by the Rack and pinion gear mechanism. The electrical and electronic parts control the system and apply the force to the soil, measure the pressure-sinkage of soil data, and process, and record the measurement data. An electric motor with a power of 5.5 kW and a nominal speed of 1430 rpm was utilized to start the system and supply the driving force. In addition to a worm gear reducer with three-speed reduction ratios (6, 12, and 19), an inverter (LS, produced by LG in South Korea) was used to control the rotational speed of the electric motor. By combining the 1:19 reduction ratio of the gearbox with the frequency adjustment of the inverter, three desired sinkage rates of 15, 30, and 45 mm/s were obtained for the experiments. To measure the force applied to the probes, an S-shaped load cell (Bongshin DBBP, made in South Korea) with a nominal capacity of 1000 kg and an accuracy of 0.02 kg was used for the experiments. A linear encoder (ATEK MLC320, made in Turkey) was utilized to measure the amount of soil deformation (sinkage). The displacement measurement system of the linear encoder is magnetic with a measurement length of 400 mm, a maximum movement speed of 300 mm s^{-1}, and a repeatability of ± 1 pulse (Mahboub Yangeje & Mardani Korani, 2021).

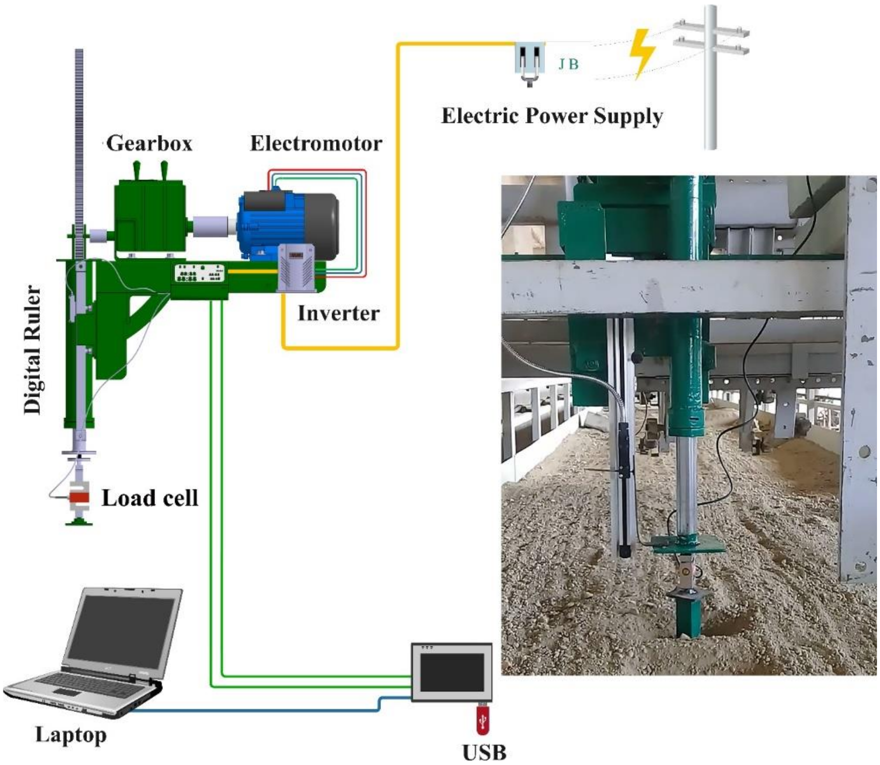

Fig.1. Bevameter installed on the soil bin carrier

Considering that the shape of the loading plates affects the pressure-sinkage relationship, the aspect ratio of the loading plates is considered in the standard range of

1.4-6, which is similar to Bekker's term pressure-sinkage patterns (Van *et al.,* 2008). The dimensions of the rectangular plates for experimental tests were 175×70 and 105×70 mm^2.

Eq. 2 is used to determine the output speed of the electric motor that is applied to the input of the gearbox to control the speed of the probe and the velocity value included in Eq. 2 for obtaining the electric motor rotation value corresponds with this speed.

$$n = \frac{i \times V \times 60}{75} \quad (2)$$

Where, n is the prediction of the rotational output speed of the electric motor, which is applied based on the sinkage rate of the plate to the gearbox input and is in revolutions per minute, i is the transmission ratio of the gearbox, and V is the optimal sinkage velocity for the test, for which three velocities of 15, 30, and 45 mm s^{-1} were used in the tests. The number 75 is a constant in the formula and represents the displacement ratio of the rack per rotation of the pinion in millimeters.

In this research, one of the Bekker loading plates was installed on the device at each stage of the experimental tests to measure soil parameters. Force is applied to the plates based on the defined conditions. The force-displacement values were simultaneously recorded in the data logger by the load cell and the digital ruler. The files recorded by the data logger were extracted as text files and transferred to the MATLAB software (Version 9.2.0.5, MathWorks) for processing. The dependent (output) variable and the independent variables (inputs) and their levels are shown in Table 1.

Table 1- Summary of inputs and output variables ranges

Input (Independent variables)	Parameter	Unit	Levels		
1	Pressure	kPa	0-250		
2	Velocity	mm s^{-1}	15	30	45
3	Plate width	mm	105	175	
Output (dependent variable)					
1	Sinkage	mm			

The soil bin was filled with clay-loam soil, which has the same texture and characteristics (Table 2) as that of the natural soil in the geographical area of the laboratory where the study took place.

Table 2- Physical characteristics of the soil in the test soil bins

Parameter	Value
Sand	35%
Silt	22%
Clay	43%
humidity	10%
Bulk density	2630 kg m^{-3}
Young's modulus	0.3 MPa
Poisson's ratio	0.29
The angle of internal friction	32
Liquid limit	42.7%
Plasticity index	13.3%

After preparing the test setup, experiments were performed in three repetitions for each level of sinkage rate. Each of the plates was installed on the Bevameter and the force was applied to the plate. The force-displacement values were recorded simultaneously with the load cell sensors and the linear encoder in the data logger.

Deep neural network presentation

The advanced capabilities of deep learning methods have made it possible to predict the interaction between soil and tools accurately without the need for simplification or the removal of influential factors. Predicting these interactions with DNNs using inputs (independent variables) has an undeniable advantage over traditional methods. The Gray Wolf Optimization (GWO) algorithm, known for its effectiveness in optimization tasks, was utilized to fine-tune the structure and hyperparameters of the DNN. In the methodology of deep neural networks (DNN) used in this study, two approaches were employed to determine the hyperparameters of the neural network. In the first approach, a trial and error method was used to determine the total number of neurons in the hidden layers, as well as the learning rate and momentum. In the second approach, the GWO algorithm was utilized to determine the optimal architecture, momentum, and learning rate in the DNN. In the first approach, the number of hidden layers for each layer increased linearly from one to 15, and the best topology with the lowest MSE was selected as the neural network architecture. This dataset consisted of 1488 data points, and a total of 225 repetitions for each training was conducted with 1000 iterations. 15 percent of the data were randomly separated as unseen data to assess the performance of the neural network after training. Of the remaining dataset, 68% of the data was used as training data, 17% as validation data, and 15% as test data. Since the actual outputs for performance assessment after training are available, this type of data division ensures that the network is not overtrained. In Table 3, the statistical information and the span of input data are shown for the training, validation, and test sections, respectively. According to this statistical data, it can be seen that the data used for each stage of training, validation, and testing are uniform and consistent under the effects of pressure, velocity, the width of plates, and sinkage. Additionally, the standard deviation values for each variable can be seen in Table 3.

Table 3- Statistical properties of training, validation, and testing samples

Partition	Source	Minimum	Maximum	Mean	Standard deviation
Training	Pressure	3.04	249.88	118.34	66.39
	Velocity	15	45	30	11.75
	Plate width	105	175	140	35
	Sinkage	0.87	70	34	20.26
Validation	Pressure	3.39	245.18	115.84	65.80
	Velocity	15	45	30	12.7
	Plate width	105	175	140	35.05
	Sinkage	0.85	70	33.27	19.86
Testing	Pressure	3.96	249.30	126.67	69.26
	Velocity	15	45	30	11.95
	Plate width	105	175	140	35.10
	Sinkage	0.78	70	36.66	21.24

To train the network using the GWO algorithm, in the first step, the algorithm was applied to the hidden layers to achieve the best topology. Three different structures of the algorithm with 5, 10, and 15 gray wolves were used, with 20 iterations for each topology and 500 iterations for network training. In the second step, the GWO algorithm was employed on the selected topology to determine the optimal values for the learning rate and momentum. The optimization algorithm design in this stage was similar to the first stage. The search range for the number of neurons in each hidden layer for the GWO algorithm was set to 30. The overall schematic of the DNN using the GWO algorithm to find the most optimal arrangement of neurons in the hidden layers and to find the best learning rate and momentum values is shown in Fig. 2.

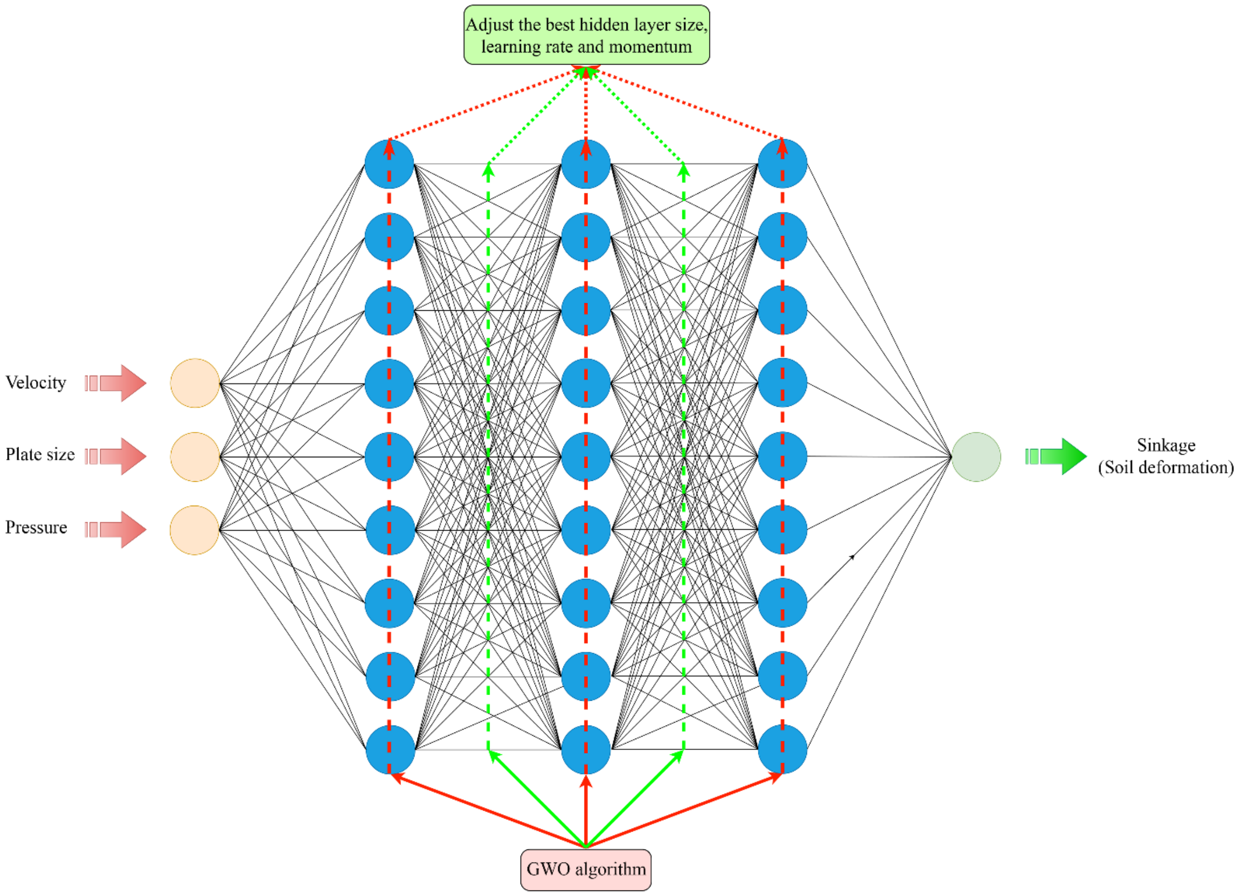

Fig.2. General multilayer perceptron DNN forward configuration with three hidden layers and applying the gray wolf algorithm to obtain the best network topology and set the learning rate and momentum

The performance of the DNN during the training, validation, and testing stages was evaluated using the Mean Squared Error (MSE), defined as Eq. 3.

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(Y_i - \hat{Y}_i)^2 \quad (3)$$

Here, Y_i is the output from the field experiment (actual value) $\hat{Y}_i$ is the output obtained by the neural network (predicted value), and n is the number of iterations used in each step. Smaller values of MSE indicate better performance of the DNN. Therefore, the values close to zero were the basis of decision-making for the better performance of the neural network (Taghavifar *et al.*, 2015).

Results and Discussion

The selection of the learning algorithm for the neural network, specifically using the backpropagation algorithm, along with the choice of the activation function, is among the most crucial settings of the DNNs to achieve suitable convergence. The sigmoid activation function was selected for all three hidden layers. To choose the learning algorithm, a trial and error approach was employed, testing seven back propagation-based learning algorithms. The algorithm that resulted in the lowest Mean Squared Error (MSE) was used as the learning algorithm in the network. The results of training the neural network with various learning algorithms are presented in Table 4.

Table 4- Training functions and performance of neural networks developed based on train functions

Transfer function	Training algorithms	R	MSE
trainlm	Levenberg-Marquardt backpropagation	0.99900	0.0837
trainrp	Resilient backpropagation	0.99965	0.2711
traincgp	Conjugate gradient backpropagation with Polak-Ribiére updates	0.99955	0.3821
traingda	Gradient descent with adaptive learning rate backpropagation	0.99349	4.5175
traincgb	Conjugate gradient backpropagation with Powell-Beale restarts	0.99966	0.2884
trainoss	One-step secant backpropagation	0.99961	0.3156
trainbr	Bayesian regularization backpropagation	0.99987	0.1084

As inferred from Table 4, the Levenberg-Marquardt learning function exhibited better performance compared to other learning functions. Therefore, this algorithm was selected as the learning algorithm. It should be mentioned that all the training steps of both types of networks used in this research are similar.

As previously mentioned, one of the selected methods for determining the hyperparameters was the utilization of the GWO algorithm. The values obtained from the output of the GWO algorithm were compared with each other to select the best topology. Table 5 shows the output of the DNN from the output of the GWO algorithm.

Table 5- Features obtained in DNN training with different combinations of the number of wolves and topologies

DNN Property	GWO-Numbers of wolf								
	5	10	15	5	10	15	5	10	15
DNN-Topology	3-8-15-10-1			3-15-10-29-1			3-23-4-18-1		
Best Momentum	0.8759	0.8646	0.2605	0.5323	0.1614	0.4105	0.3045	0.9566	0.9026
Best Learning rate	0.2375	0.1263	0.5832	0.8797	0.3137	0.7187	0.6409	0.7538	0.2042
Mse Training	0.0919	0.0837	0.0991	0.0918	0.1091	0.0986	0.0969	0.0934	0.0973

As seen in Table 5, the best performance of the neural network corresponds to the topology 3-8-15-10-1, which has three inputs consisting of the penetration rate of pages into the soil, page size, and the vertical pressure applied to the pages. The network structure includes 8 neurons in the first hidden layer, 10 neurons in the second hidden layer, and 15 neurons in the third hidden layer, with the output representing soil deformation. Furthermore, the optimal values were found to be 0.864628 for momentum and 0.126314 for learning rate resulting in a mean squared error of 0.089405. The best results were achieved when the population of gray wolves in the GWO algorithm was set to 30.

Table 6 shows the soil parameters using Bekker's method at different speeds which are extracted using Eq. 1 and the data obtained from the experimental tests. The Bevameter test method lacks standardized testing procedures and requires further investigation into the factors influencing the tests (Kruger *et al.,* 2023). Sinkage rate is considered one of the key factors in modeling the dynamics of soft soil. Table 6 presents the effects of variations in sinkage rate on determining soil parameters.

Table 6- Soil parameters with the Bekker's method at different velocities

Bekker′s constant	Velocity (mm s^{-1})		
	15	30	45
K_φ (kN/m^{n+2})	205.368	236.338	254.304
K_c (kN/m^{n+1})	19.088	21.165	21.259
n	0.745	0.713	0.748

From Table 6, it can be concluded that the soil cohesion modulus (K_C) and the soil friction modulus (K_φ) both increase with the increase in the penetration speed of the plates. However, the n (sinkage exponent) does not change significantly. These results confirm that soil constants are related to sinkage rate. Fig. 3 shows the neural network regression diagram for the training, validation, and test data. Our regression analysis demonstrates the effectiveness of our DNN model in predicting changes in soil deformation resulting from Bevameter penetration, aimed at better-characterizing soil parameters using the Bekker method. Figs 3. a-c depict scatter plots of predicted soil deformations against actual values for the training, validation, and testing datasets, respectively. Notably, the correlation coefficients (R) of these plots accentuate a strong linear relationship, with values of 0.9999 for training, 0.99983 for validation, and 0.99978 for testing. These high R values affirm the model's commendable performance in predicting soil deformation. It effectively converges, avoids significant overfitting, and generates unbiased predictions, as evidenced by the regression plots. This analysis emphasizes the potential of our model for accurately predicting soil deformation, with applications in soil parameter estimation using the Bekker method.

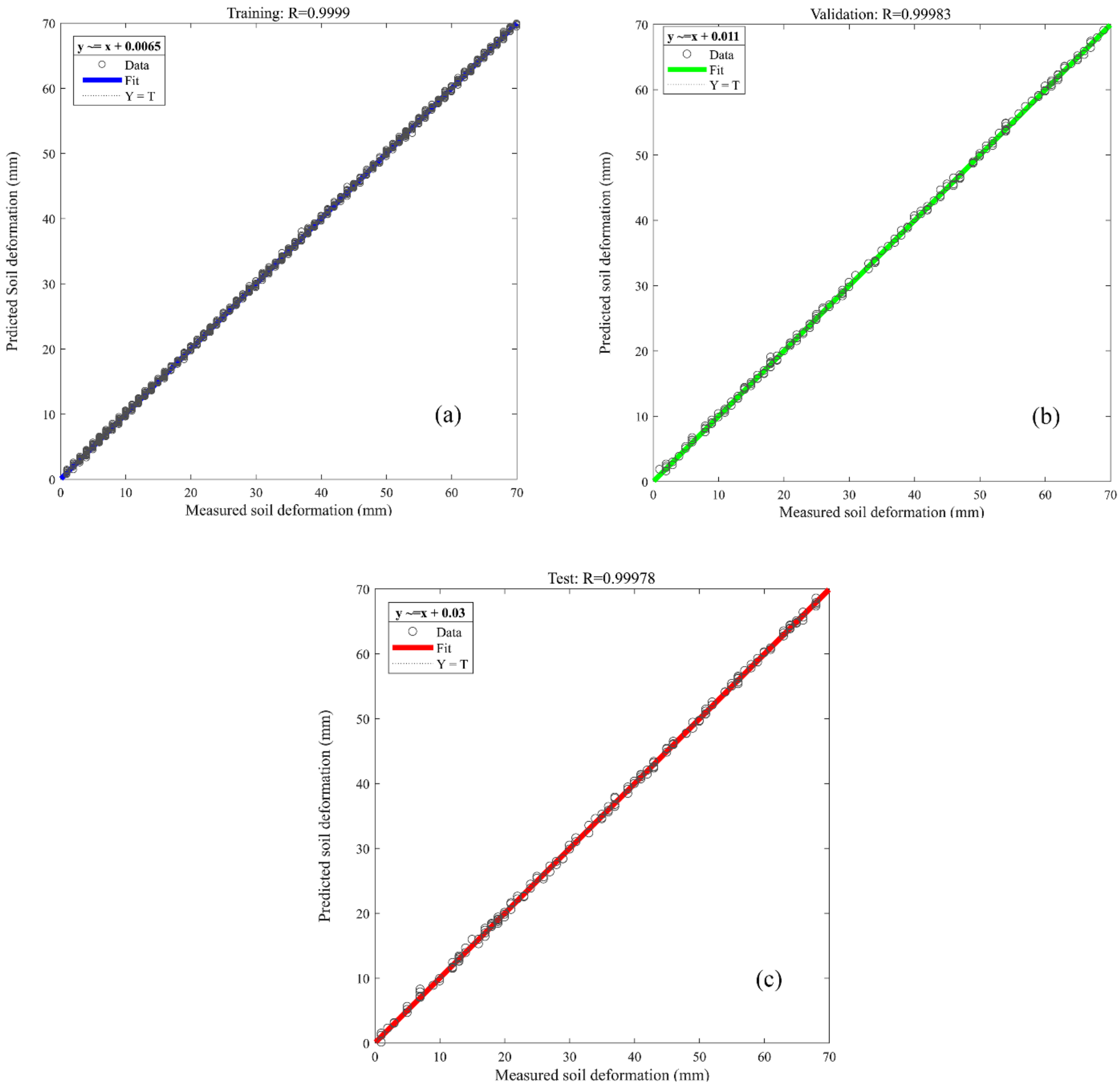

Fig.3. Regression results for neural network a. training, b. validation, and c. test data

Before starting the neural network training process, we used a cautious approach to increase the generalization capabilities of the model. We did this by randomly setting aside 15% of our data set, a common practice known as data partitioning, to serve as a validation set. By isolating a subset of the data that was not used in the model during training, we develop a measure to assess its ability to generalize beyond the examples it was exposed to during the learning phase. Essentially, the neural network was tested on this unseen data to assess its capacity to make accurate predictions beyond the scope of the training dataset. The successful results show that our model effectively learns the underlying patterns and relationships in the data without merely memorizing. Instead, it has understood the fundamental features, allowing it to generalize and make reliable predictions for new scenarios of soil deformation. This validation step is essential in any machine learning task, especially in the field of soil parameter estimation using Bekker's method. This strengthens our confidence in the model's capabilities and its potential for real-world application. Additionally, it protects the model against issues such as overfitting, where a model overfits the training data and performs poorly on new, unseen data (Fig. 4).

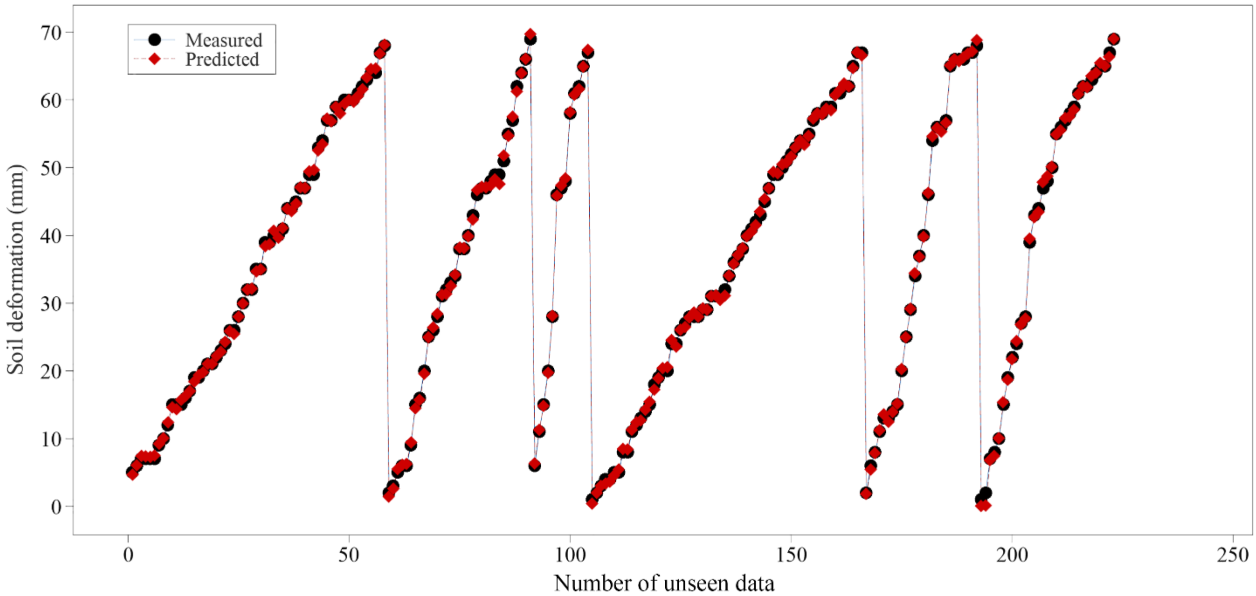

Fig.4. Trend of experimental and predicted values for soil deformation with unseen data

Figs. 5 and 6 show that sinkage increases with increased penetration velocity and pressure, for plates with 105 and 175 mm widths, respectively.

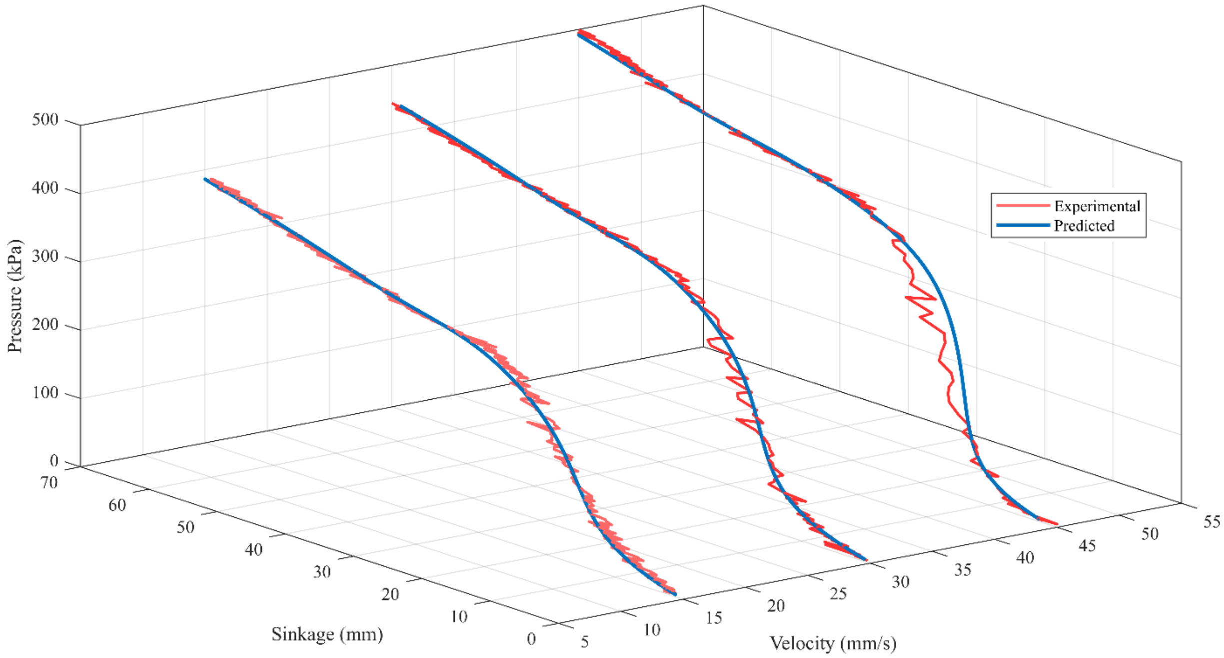

Fig.5. Pressure-sinkage diagrams for 105 × 70 (mm^2) plate size and velocities of 15, 30, and 45 mm s^{-1}

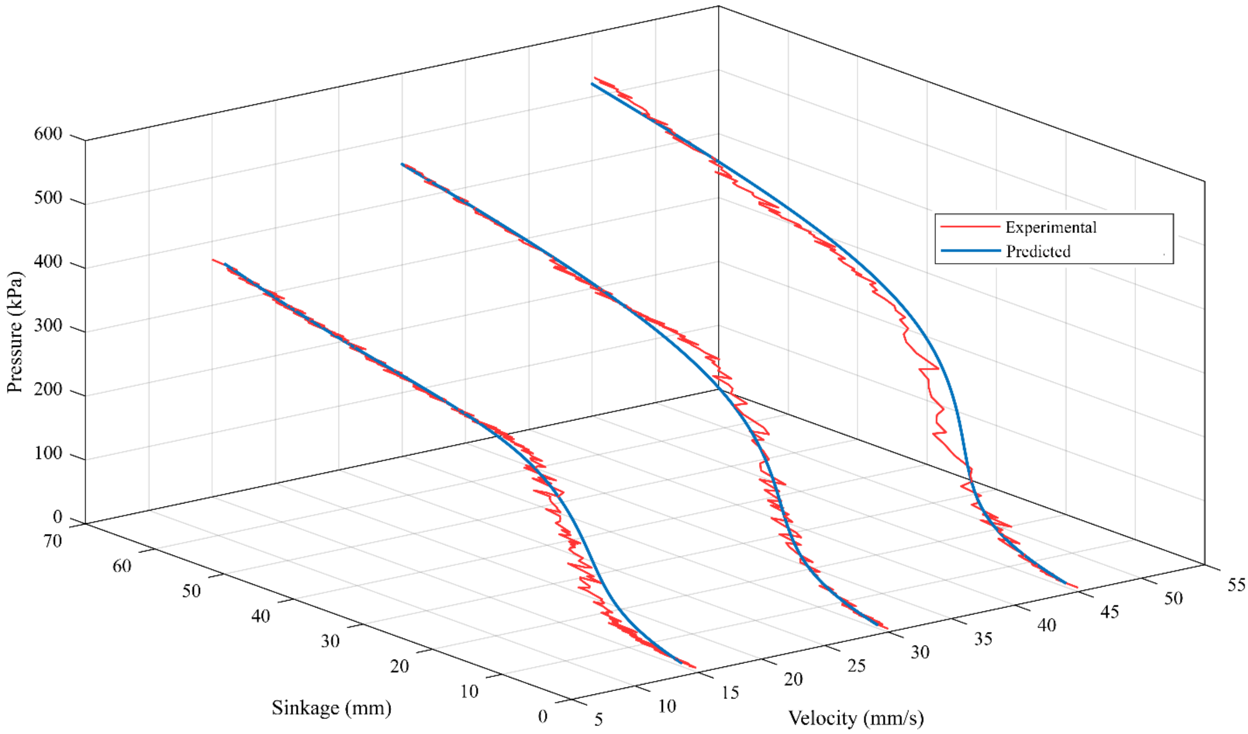

Fig.6. Pressure-sinkage diagrams for 175 × 70 (mm^2) plate size and velocities of 15, 30, and 45 mm s^{-1}

In Figs. 5 and 6, considering the trend of pressure-sinkage changes, empirical data has been utilized, and neural network-fitted (predicted) graphs have been employed. It is observed that the neural network has been effectively trained and accurately predicts the pattern of empirical data. Furthermore, it shows that varying penetration rates result in different pressure-sinkage patterns. This notably indicates that the penetration rate plays a role in determining soil parameters. Another inference drawn from Figures 5 and 6 is that to achieve a consistent settlement after a depth of 20 to 30 millimeters, the pressure on the plates must increase with the penetration rate. Therefore, by reducing the penetration rate, a lower pressure can be applied to the plates to achieve the same depth.

In this study, three methods (Bekker model, deep neural network with hyperparameters tuning using trial and error, and deep neural network with hyperparameters determination using the Gray Wolf Optimization algorithm) were employed to determine the soil parameters at different speeds. The performance comparison of these three methods is presented in Table 7.

Table 7- Comparison of three models to estimate soil parameters

Method	MSE	RMSE
DNN-GWO	0.0837	0.2893
DNN-trial-error	1.18	1.0862
Bekker	17.30	4.1593

As it is clear from Table 7, the deep neural network achieved by adjusting the hyperparameters using the gray wolf method has performed significantly better than the other models. Using the GWO algorithm to determine the size of hidden layers in DNNs has significant advantages. It optimizes DNN architectures, which ultimately results in highly accurate models with lower mean squared error (MSE). This not only increases the predictive capability and performance of the neural network but also saves time and computational resources by automating the architecture optimization process. GWO also avoids overfitting, exploring a wide range of architectures that potentially yield superior results. Overall, GWO simplifies the process and makes DNN design more efficient and effective.

Networks trained with GWO-optimized learning rates tend to generalize better and require less manual hyperparameter tuning. Similarly, GWO's role in optimizing momentum leads to faster convergence, improved generalization, and a reduction in manual tuning efforts, ultimately streamlining neural network training and enhancing model performance.

Conclusion

To investigate the impact of factors such as the sinkage rate of plates, applied pressure on the plates, and the size of the plates on soil parameters within a soil bin, a Bevameter was employed. Experiments were conducted at three levels of penetration velocity: 15, 30, and 45 mm s^{-1}, with two plate sizes, and under dynamic loading conditions. To predict the soil sinkage with different inputs, a Multi-Layer Perceptron (MLP) deep neural network with the Backpropagation (BP) algorithm was optimized and trained using the Grey Wolf Optimization algorithm for neuron count, momentum, learning rate, and the trial and error method for learning algorithms. The optimal neural network topology had a structure of 3-8-10-15-1, consisting of three inputs and three hidden layers with the sigmoid transfer function. The development of the DNN yielded the following results:

1. A deep neural network with a structure of 3-8-15-10-1 with three inputs (sinkage rate, applied pressure on the plates, and plate size) successfully estimated sinkage with high accuracy.
2. Increasing the sinkage rate of plates resulted in higher soil modulus values.
3. A lower plate sinkage rate requires less force to reach a specific depth. In other words, for plates with fixed dimensions, to achieve the same sinkage after passing a depth of 20-30 millimeters, greater pressure on the plates is required for achieving higher plate sinkage rates.
4. The Bekker equation, in its original form, does not account for the sinkage rate parameter of the soil. Based on this research's findings, it is advisable to

consider the influence of this factor and incorporate plate sinkage rate into the equation. For achieving more accurate and realistic Bekker equation parameters, a standard sinkage rate for the plates should be considered in this context.

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مدل‌سازی فشار- نشست خاک تحت تأثیر سرعت نشست با استفاده از یادگیری عمیق بهینه‌سازی‌شده توسط الگوریتم گرگ خاکستری

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چکیده

با توجه به متغیرهای متعددی که بر سیستم‌های اندرکنش خاک و ماشین تأثیرگذار هستند، پیش‌بینی پاسخ مکانیکی خاک در تعامل با دستگاه‌های کششی خارج از جاده چالش برانگیز است. در این مطالعه، شبکه‌های عصبی عمیق به دلیل توانایی آن‌ها در مدل‌سازی سیستم‌های پیچیده، چندمتغیره و دینامیک به‌عنوان یک راه‌حل بالقوه برای توضیح میزان فرورفتگی خاک در نرخ‌های مختلف از بار عمودی انتخاب شد. آزمایش‌های فشار-نشست خاک با استفاده از بوامتر در یک انباره خاک از نوع ثابت با طول ۲۴ متر، عرض ۲ متر و کانال خاک عمق ۱ متر انجام شد. آزمایش‌های تجربی در سه سطح سرعت نشست، دو سطح اندازه صفحه، در محتوای آب خاک ۱۰ درصد انجام شد که داده‌های تجربی در مورد روابط فشار و نشست خاک ارائه می‌کرد. این آزمایش‌ها به‌عنوان مبنایی برای الگوریتمی بود که قادر به تشخیص تعامل بین خاک ماشین پس از یک فرآیند تکراری دقیق بود. مشخص شد که یک شبکه عصبی عمیق، به‌ویژه یک شبکه عصبی عمیق با انتشار پیش‌خور با سه لایه پنهان، انتخاب بهینه برای این منظور است. معماری شبکه عصبی عمیق بهینه‌شده به‌صورت ۱-۱۰-۱۵-۸-۳ شکل یافت که توسط الگوریتم بهینه‌سازی گرگ خاکستری تعیین شده است. در حالی‌که معادله بکر به‌طور سنتی به‌عنوان یک روش پذیرفته‌شده برای پیش‌بینی رفتار فشار- نشست خاک استفاده می‌شود، تأثیر سرعت نشست در خاک را نادیده می‌گرفت. با این حال، یافته‌های تحقیق تأثیر قابل‌توجهی از سرعت نشست بر پارامترهای حاکم بر پاسخ تغییر شکل خاک را نشان داد. شبکه عصبی عمیق آموزش‌دیده با موفقیت سرعت نشست را در ساختار خود گنجاند و نتایج دقیقی با مقدار میانگین مربعات خطای ۰/۰۸۷۱ ارائه کرد.

واژه‌های کلیدی: انباره خاک، بوامتر، ترامکانیک، شبکه عصبی عمیق، وسیله نقلیه خارج از جاده

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