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THE USE OF ARTIFICIAL INTELLIGENCE METHODS FOR OPTIMIZATION OF TRACTIVE PROPERTIES ON SILTY CLAY LOAM

Summary

The aim of this study was to develop valuable model of the interaction between low-power tractors wheel and deformed ground as well as to optimize tractor performance on silty clay loam. The relationships between traction force as well as traction efficiency and soil moisture, soil compaction, horizontal deformation, and vertical load were the subject of investigation. The research was carried out in the laboratory conditions. The two soft computing techniques of mathematical modeling were used: multilayer perceptron and radial basis function neural network. The more efficient model was obtained by multilayer perceptron. For the model with traction force as the output parameter the coefficient of determination was equal to 0,963 (MLP model) and 0,907 (RBF model). For the model with traction efficiency as the output parameter the coefficient of determination was equal to 0,986 and 0,944, respectively. Using the MLP model, the sensitivity analysis was conducted. The highest relative influence on traction force was observed for vertical load, in the case of traction efficiency, horizontal deformation is the most important parameter. For both dependent variables the lowest influence was calculated for soil compaction. The optimization of tractive properties requires generally high horizontal deformation, average soil moisture and high soil compaction. High vertical load is necessary for traction force maximization and relatively low for traction efficiency optimization.
***Key words**: traction force, traction efficiency, artificial neural network, genetic algorithm*

METODY SZTUCZNEJ INTELIGENCJI W OPTYMALIZACJI WYBRANYCH WŁAŚCIWOŚCI TRAKCYJNYCH NA GLEBACH GLINIASTYCH

Streszczenie

Celem pracy było wygenerowanie możliwie dokładnych modeli opisujących interakcję układu opona napędowa–gleba gliniasta dla mikrociągnika. Na podstawie wygenerowanych modeli przeprowadzono optymalizację pracy analizowanego układu. Badaniom podlegały zależności między siłą i sprawnością trakcyjną a wilgotnością i zwięzłością gleby, deformacją poziomą i obciążeniem pionowym. Badania przeprowadzono w warunkach laboratoryjnych. W zadaniu modelowania matematycznego wykorzystano dwie techniki sztucznej inteligencji: sieć neuronową typu perceptron wielowarstwowy (MLP) oraz sieć neuronową z radialnymi funkcjami bazowymi (RBF). Bardziej dokładny okazał się model oparty o sieć MLP. Współczynnik determinacji opisujący jakość modelu w przypadku siły trakcyjnej wynosił 0,963 (model MLP) i 0,907 (model RBF). W przypadku sprawności trakcyjnej współczynnik determinacji wyniósł odpowiednio 0,986 i 0,944. Wykorzystując modele oparte na sieci MLP przeprowadzono analizę wrażliwości modeli. Analiza ta wykazała, że największy wpływ na siłę trakcyjną ma obciążenie pionowe, a w przypadku sprawności trakcyjnej najbardziej znaczącym parametrem jest deformacja pozioma. Dla obu zmiennych zależnych, najmniej znaczącym parametrem jest zwięzłość gleby. Optymalizacja parametrów trakcyjnych wymaga generalnie dużej wartości deformacji poziomej, średniej wartości wilgotności i dużej zwięzłości gleby. Maksymalizacja siły trakcyjnej jest możliwa przy dużej wartości obciążenia pionowego, a optymalną wartość sprawności trakcyjnej można uzyskać przy niskiej wartości obciążenia pionowego.
***Słowa kluczowe**: siła trakcyjna, sprawność trakcyjna, sztuczne sieci neuronowe, algorytm ewolucyjny*

1. Introduction

Tractors are considered as the main machines that generate power for field operations in agriculture. Research shows that 20–55% of tractor's power is lost because of the interaction between tyres and topsoil [1]. The minimization of energy loss and maximization of energy efficiency of tractors is essential in modern agriculture. The unnecessary loss of energy means an increase of fuel consumption and greenhouse gas emissions. Therefore, the optimization of tractor performance is crucial in the aspect of economy and environmental protection. There are some parameters pointed out in the literature as affecting the tractor performance: tyre inflation pressures, wheel slip and vertical wheel loads [2, 3, 4]. The majority of the research on topsoil-tyre interactions was carried out for high-power tractors. However, low-power tractors are more and more popular, especially in horticulture and maintenance of green spaces. Therefore, in this research, the interaction between soil and the traction device for low-power tractors was investigated.

Mathematical modeling of the topsoil-tyre interaction can produce models of high accuracy, based on empirical, semi-empirical and analytical methods [5]. Because of the complexity of the interaction between tire and soil, there are some difficulties in the development of semi-empirical and analytical models. Empirical models are simpler to develop, but can be applied only in conditions similar to those, which were used for model preparation. The development of accurate models models of the soil-tyre interaction is essential for tractor performance optimization. Only exact mathematical model can be used as objective function for optimization algorithm. When relationships under study are complex and nonlinear, some soft computing techniques such as artificial neural networks (ANN) can be used for model development. This technique was employed by some researchers for modeling soil-tire interaction [6, 7].

The objective of this study was to employ two the most popular ANN architectures: multilayer perceptron (MLP) and radial basis function (RBF) to estimate traction force and traction efficiency of a low-power tractor as a function of vertical load, horizontal deformation, soil compaction, and soil moisture on silty clay loam. Based on high precision models, the analysis of predictor variables importance was conducted and an evolutionary algorithm was employed for traction conditions optimization.

2. Research methodology

2.1. Experimental data acquisition

The tests were carried out in laboratory conditions on silty clay loam. The levels of soil moisture (changed in a controlled manner by water addition) were as follows: 1.25 field water capacity, field water capacity, beginning of plant growth inhibition and strong inhibition of plant growth. Soil compaction was changed by means of special stand by altering compaction time. A soil bin testing facility is presented in Fig. 1.

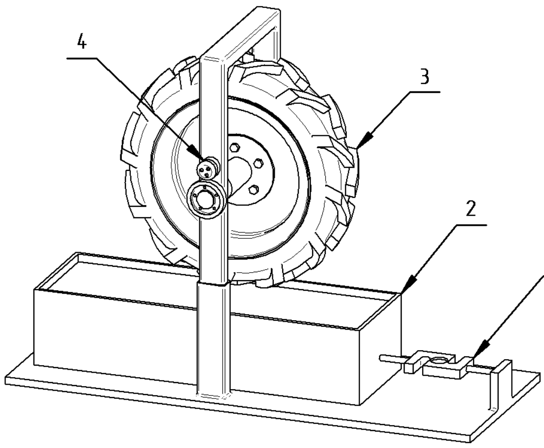

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Fig. 1. The scheme of a soil bin testing facility: 1- tensometric rectifier of power, 2- box with soil, 3- wheel, 4- linear potentiometer

Rys. 1. Schemat stanowiska pomiarowego: 1- tensometric rectifier of power, 2- pojemnik z glebą, 3- koło, 4- potencjometr

The vertical load of the wheel was changed by means of a wheel bevameter. Measurements were conducted using one tyre type of the size 4.50-10, with maximum carrying capacity of 932 N. The value of soil horizontal deformation was calculated on the basis of the ratio of the static radius of the wheel and the angle of its turn. Tractive force was measured with the use of a tensometric power rectifier. Traction efficiency was calculated as follows:

$$\eta = \frac{\int_0^j P_T(j)dj}{\int_0^j P_T(j)dj + G \cdot h} \tag{1}$$

where: η is the traction efficiency, P_T is the traction force [N], j is the horizontal deformation [m], G is the vertical load of the wheel [N] and h is the vertical immersion of the tyre [m]. The methodology of performed experiments is detailed in [8].

The statistics of experimental data are presented in Table 1.

Table 1. Statistics of experimental data

Tab. 1. Statystyki podstawowe danych uzyskanych w trakcie pomiarów

The parameter	Minimum	Maximum	Mean	Standard deviation
Horizontal deformation [m]	0,01	0,05	0,03	0,01
Vertical load [N]	375,00	932,00	644,00	199,53
Soil compaction [kPa]	95,89	520,83	308,36	128,13
Soil moisture [%]	19,00	38,00	28,50	6,81
Traction force [N]	48,83	770,65	362,24	150,15
Traction efficiency [%]	2,05	73,77	31,80	14,91

Source: the authors' study / Źródło: opracowanie własne

2.2. Artificial neural network development

Neural network structures are inspired by biology, namely the structure of human nervous system. Neural networks are mathematical models composed of simple processing components (artificial neurons) arranged in layers. In this work, two the most popular ANNs are used: multilayer perceptron (MLP) and radial basis function (RBF). In MLP network, the value of neuron output is calculated as the weighted sum of its inputs transferred by an activation function (usually sigmoid). In RBF network, neurons in hidden layer are radial basis neurons, output signal of the network is calculated by linear neuron.

Simulations were performed using *Statistica* 10 software. The input layers of both networks were composed of four nodes (vertical load, horizontal deformation, soil compaction and soil moisture). The output layers were composed of only one neuron calculating traction force or traction efficiency. During the ANN model training process, the number of neurons in the hidden layer was set to a range from 5 to 35. The transfer functions of neurons in MLP were as follows: sigmoidal, hyperbolic tangent and exponential. The transfer functions of the neurons in RBF hidden layer were Gaussian distribution.

For each model, the 500 independent ANNs were trained. The 400 data sets obtained during the measurement process, were randomly separated into training, test and validation sets as 70:15:15 ratios. The data were normalized into a range <0;1>. Model quality assessment was based on mean square error (MSE) and coefficient of determination (R^2).

2.3. Quantifying variable importance

In this work the sensitivity analysis implemented in *Statistica v. 10* was used as the method for calculation of relative importance of independent variables. It was proved, that extracting the contribution of variables based on neural networks, requires the group of neural models [9]. Therefore, in this work, the results of predictor variables contribution were calculated based on the committee of twenty ANN architectures with the highest R^2 value and the lowest MSE. The arithmetical mean of all twenty results was calculated and constituted the final result.

2.4. Optimization procedure – evolutionary algorithm

The optimization of traction conditions was conducted using Excel Solver with evolutionary algorithm implemented in *Microsoft Excel 2010* environment. In this research, algorithm parameters were set as follows: convergence – 0.0001, mutation rate – 0.075, population size – 100, random seed – 0, maximum time without improvement – 30.

3. Results and discussion

The two ANN types were used for neural models development: MLP and RBF. The best ANN architectures and parameters describing their quality are presented in Table 2. MSE values were calculated for normalized data.

The data presented in Table 2 show the high quality of neural models obtained during simulations for both dependent variables: traction force and traction efficiency. A little higher accuracy was observed for MLP model, which produced R^2 values 0,963 and 0,986 for validation data set. High R^2 values and low MSE error values mean that no overfitting occurred during training process and model can be useful for real-world applications. Values of coefficient of determination calculated for validation data set in the case of RBF model were 0,907 for traction force and 0,944 for traction efficiency. RBF model produced also low values of MSE error. Based on these results it can be stated that both ANNs produced efficient mathematical models of investigated relationships. The performance of predicted values of traction force and traction efficiency vs. the measured values in validation partition for MLP and RBF is presented in Figs. 2-5.

MLP and RBF are the most widely used neural network types for solving regression problems in engineering. These networks were used for prediction of operating time of oil in combustion engine as affected by the content of certain oil particles [10]. Generally, authors reported the MLP models as more accurate than RBF models. Similarly, the MLP technique was found as more precise compared to the Gaussian RBF technique for hazard zonation of landslides [11].

The group of ten the best MLP models with traction force and traction efficiency as output parameters were used for quantifying importance of input variables. The results are detailed in Fig. 6.

Table 2. Parameters of neural models
Tab. 2. Parametry modeli neuronowych

Dependent variable	ANN structure	Coefficient of determination R^2			Mean square error (MSE)		
		training data set	test data set	validation data set	training data set	test data set	validation data set
MLP model							
Traction force	4-24-1	0,982	0,970	0,963	0,00036	0,00063	0,00085
Traction efficiency	4-20-1	0,994	0,987	0,986	0,00012	0,00028	0,00034
RBF model							
Traction force	4-18-1	0,936	0,894	0,907	0,00132	0,00229	0,00218
Traction efficiency	4-34-1	0,942	0,918	0,944	0,00122	0,00179	0,00126

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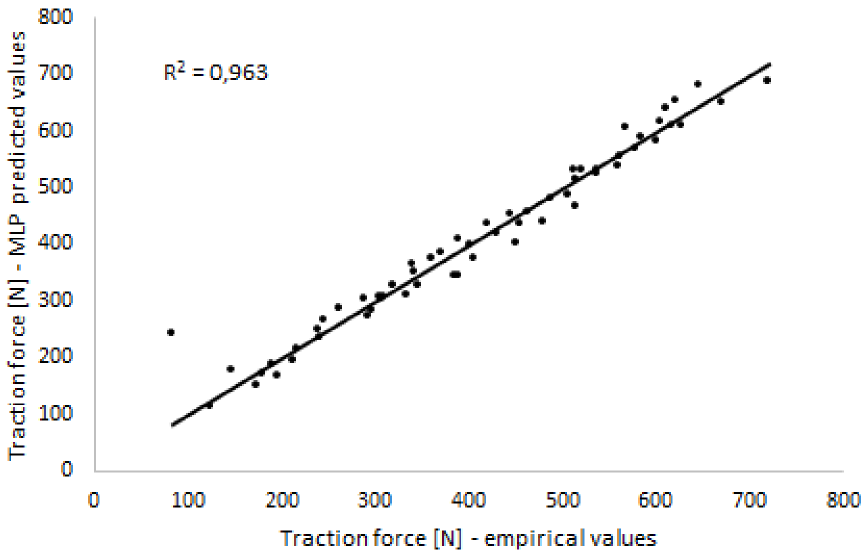

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Fig. 2. Predicted values versus measured values of traction force (validation data set, MLP model)
Rys. 2. Zależność między wartościami siły trakcyjnej obliczonymi za pomocą modelu i uzyskanymi z pomiarów (zbiór walidacyjny, model MLP)

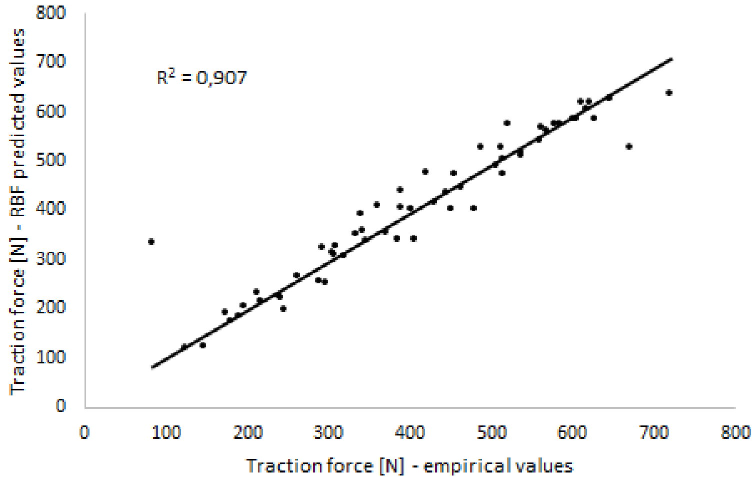

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Fig. 3. Predicted values versus measured values of traction force (validation data set, RBF model)

Rys. 3. Zależność między wartościami siły trakcyjnej obliczonymi za pomocą modelu i uzyskanymi z pomiarów (zbiór walidacyjny, model RBF)

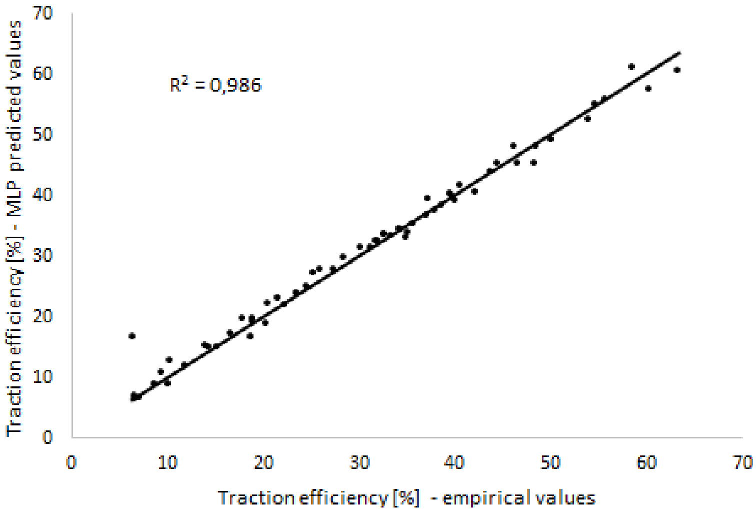

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Fig. 4. Predicted values versus measured values of traction efficiency (validation data set, MLP model)

Rys. 4. Zależność między wartościami sprawności trakcyjnej obliczonymi za pomocą modelu i uzyskanymi z pomiarów (zbiór walidacyjny, model MLP)

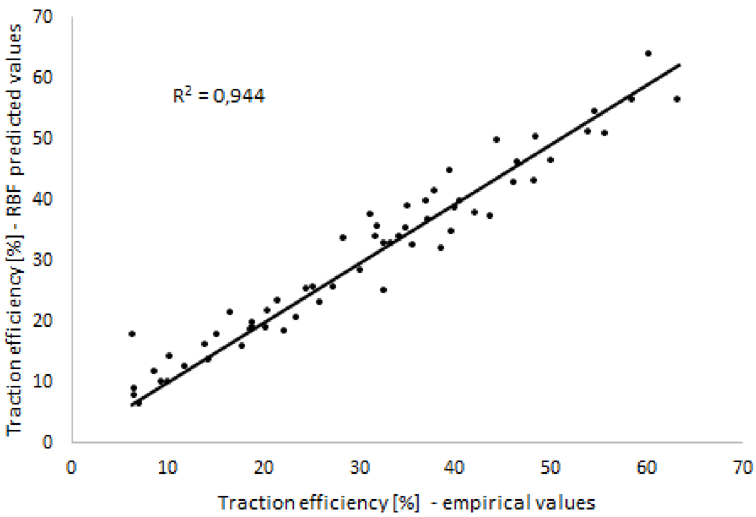

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Fig. 5. Predicted values versus measured values of traction efficiency (validation data set, RBF model)

Rys. 5. Zależność między wartościami sprawności trakcyjnej obliczonymi za pomocą modelu i uzyskanymi z pomiarów (zbiór walidacyjny, model RBF)

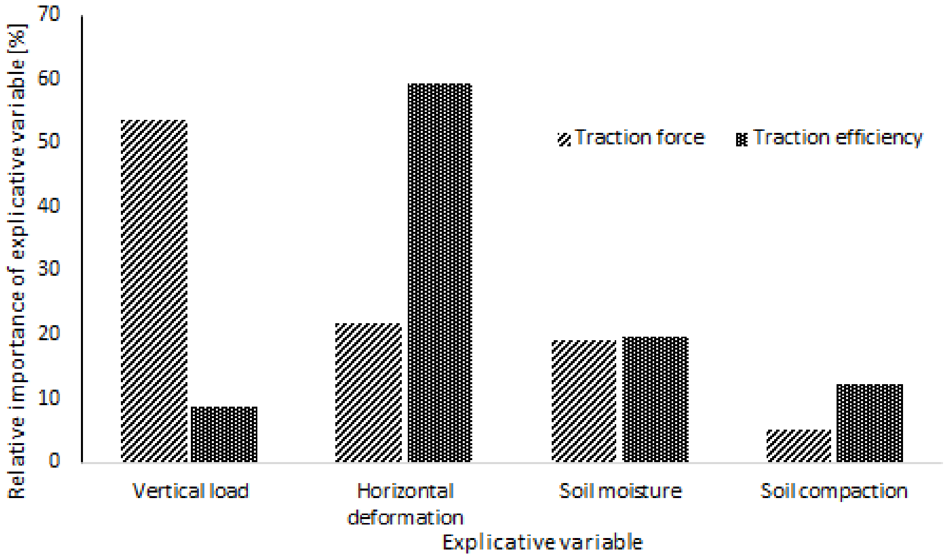

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Fig. 6. Average variable relative importance in traction force and traction efficiency models

Rys. 6. Średni procentowy wpływ zmiennych niezależnych na siłę trakcyjną i sprawność trakcyjną

Vertical load is the most important parameter influencing traction force (53,7%). This parameter affects traction efficiency only in 8,6%. Horizontal deformation which influences traction efficiency the most (59,4%), affects traction force in 21,8%. The influence of soil moisture on traction force and traction efficiency is similar, 19,2% and 19,8% respectively. Soil compaction is the least important parameter for both tractive properties. Some other authors investigated the influence of different parameters on tractive properties. Vertical load was pointed out as important parameter influencing the rolling resistance [4] and the traction coefficient as well as the tractive power efficiency [12]. Additionally, it is easily managed parameter.

Based on MLP models, the optimization process of traction force and traction efficiency was performed with evolutionary algorithm. The aim of optimization was to calculate the values of vertical load, horizontal deformation, soil moisture and soil compaction which produce the maximum of traction force and traction efficiency. The range of independent variables was the same as during measurements (Table 1). First, all independent variables were calculated by evolutionary algorithm in order to optimize tractive properties. Then, optimization process was performed with assumption that soil moisture or soil compaction was a constant parameter and only three independent variables were calculated. The results of the optimization process, are presented in Table 3.

Table 3. Optimum parameters calculated for tractive properties

Tab. 3. Wartości zmiennych niezależnych obliczone w procesie optymalizacji właściwości trakcyjnych

Traction force optimization				
Vertical load [N]	Horizontal deformation [m]	Soil compaction [kPa]	Soil moisture [%]	Traction force [N]
All independent variables are calculated				
931,96	0,05	520,82	26,70	692,69
Soil moisture is a constant parameter				
932,00	0,02	520,82	19 = min	687,63
931,99	0,05	412,98	38 = max	686,91
Soil compaction is a constant parameter				
932,00	0,05	95,89 = min	35,51	676,81
932,00	0,05	520,83 = max	26,78	691,24
Traction efficiency optimization				
Vertical load [N]	Horizontal deformation [m]	Soil compaction [kPa]	Soil moisture [%]	Traction efficiency [%]
All independent variables are calculated				
467,94	0,05	444,76	23,19	67,24
Soil moisture is a constant parameter				
497,68	0,05	491,30	19 = min	67,24
493,01	0,05	520,82	38 = max	67,24
Soil compaction is a constant parameter				
932,00	0,05	95,89 = min	20,46	67,24
375,00	0,05	520,83 = max	23,74	67,24

Source: the authors' study / Źródło: opracowanie własne

The data presented in Table 3 show that both tractive properties can be maximized with generally high value of horizontal deformation, average soil moisture and high soil compaction. The optimal traction force can be produced with high vertical load and optimal traction efficiency – with rather low vertical load. The vertical load is the most easily managed parameter during agricultural operations with tractor. Therefore, in order to achieve optimal tractive properties, the compromise has to be found. Furthermore, it is very difficult to change soil compaction and soil moisture before agricultural operations (sometimes the operation can be only advanced or delayed). However, authors tried to calculate the optimal values of independent model parameters when one input value: soil moisture or soil compaction reaches its maximum or minimum. In the case of traction force optimization, the strong reduction of horizontal deformation is required for the minimum value of soil moisture, and little reduction of soil compaction is needed when soil moisture is maximum. When soil compaction changes from maximum into minimum value, soil moisture should increase to its almost maximum value. In the case of traction efficiency optimization, the strong change of soil moisture doesn't affect other parameters and strong change of soil compaction influences significantly the vertical load.

4. Conclusions

Artificial intelligence methods can be successfully used for modeling and optimization of tractive properties. Based on data collected during experiments, it can be stated that MLP neural network produced more efficient model that RBF neural network. However, both models can be used in practice. The calculation of explicative variables relative importance showed that vertical load is the most important parameter influencing traction force and horizontal deformation affects traction efficiency the most. Soil compaction was found as the least important parameter for both tractive properties. Both, traction force and efficiency can be maximized with generally high value of horizontal deformation, average soil moisture and high soil compaction. In the case of vertical load, it should be high for traction force maximization and relatively low for traction efficiency optimization. It is easy to calculate optimal values of vertical load and horizontal deformation with the use of evolutionary algorithm when soil moisture and compaction are constant parameters.

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