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Hossein Moayedi

Ton Duc Thang University

Amir Mosavi (amir.mosavi@kvk.uni-obuda.hu)

Ton Duc Thang University

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A Water Cycle-based Error Minimization Technique in Predicting Bearing Capacity of Foundation

Hossein Moayedi, Amir Mosavi

Atmospheric Science and Climate Change Research Group, Ton Duc Thang University, Vietnam amir.mosavi@kvk.uni-obuda.hu

Abstract

Selecting the appropriate training technique is a significant step in utilizing intelligent approaches. It becomes even more important when it comes to critical problems like analyzing the bearing capacity of foundations. This study investigates the feasibility of a capable metaheuristic algorithm, called water cycle algorithm (WCA), for training a multi-layer perceptron (MLP). The WCA-MLP is applied to a large finite element dataset to predict the settlement. The results of this model are compared with electromagnetic field optimization (EFO) and shuffled complex evolution (SCE) benchmarks. With reference to the obtained Pearson correlation factors (larger than 0.88 in all stages), all employed models are suitable for the mentioned objective. Moreover, it was observed that the training error of the WCA was 5.84 and 3.89% smaller than the EFO and SCE, respectively. Likewise, the accuracy of the WCA-MLP was 1.85 and 2.04% larger in the testing phase. Also, a predictive equation is finally elicited for practical applications in compatible circumstances.

Keywords: Bearing capacity; Settlement measurement; Artificial neural network; Water cycle algorithm.

1 Introduction

With recent advances in computational intelligence, many scholars have replaced traditional methods with economical and accurate machine learning , deep learning [1-7], decision making [8; 9], and artificial intelligence-based tools [10-14]. These novel approximation techniques are well employed in various engineering field such as in evaluating the environmental concerns [15-25], implications for natural environmental [26-34], water resources management [35-41], energy efficiency [42-50], structural design [51-61], image processing [62-65], feature selection/extraction [66-70], face recognition [71-74], control performance [75], vibration analysis [76], climate change [77], managing the smart cities [78], project management [79], while in the field of medical science artificial intelligence employed to have a better diagnosis of a particular patients [80-84], early diagnosis of

them [85; 86], or medical image classification [87]. There have been many novel algorithms enhancing the current predictive neural network-based models. Metaheuristic algorithms have been highly regarded in various problems that demand an optimal solution [85]. The hybrid optimization techniques such as differential evolution [88], data-driven robust optimization [89], whale optimization algorithm [90; 91], harris hawks optimization [88; 92], differential edge detection algorithm [93], many-objective sizing optimization [94], fruit fly optimization [95], moth-flame optimization strategy [96; 97], bacterial foraging optimization [98], ant colony optimization [99], particle swarm optimization (PSO) [100-102], chaos enhanced grey wolf optimization [82], and quantum-enhanced multiobjective large-scale [103].

The efficient determination of ultimate bearing capacity (BC) of foundations is a significant consideration in designing various structures [104-106]. Khorrami et al. [107] presented an explicit formulation for ultimate BC for foundations settled on granular soil through an M5' model tree. As an advantage, the proposed model showed lower uncertainty as well as larger efficiency in comparison with a number of conventional theories. Likewise, Khorrami and Derakhshani [108] used a hybrid of this model coupled with genetic programming for calculating the BC for a system of footing and cohesionless soil. Sethy et al. [109] introduced adaptive neuro-fuzzy inference system (ANFIS) as a capable approximator for computing the BC of rectangular footing with eccentrically loading. Also, in comparison with artificial neural network (ANN), the output pattern of the ANFIS was in a larger agreement with the expected one (the coefficients of determination of 0.9024 vs. 0.9118). The competency of support vector machine (SVM) and random forest for estimating the BC of footings placed on rocks was demonstrated by Dutta et al. [110]. Moayedi and Hayati [111] tested several soft computing approaches for exploring the BC of shallow foundations installed near homogeneous slopes. The findings revealed the excellence of the feedforward ANN compared to models like tree regression fitting and SVM. In a similar effort, Acharyya and Dey [112] investigated the feasibility of the ANN. They also analyzed the importance of effective factors using this model and found that the angle of internal friction plays the most influential role. Aouadj and Bouafia [113] embedded a new mathematical activation function and fed the proposed network by the records of the cone penetration test. Large agreements between the desired and produced outputs, as well as around 30% higher accuracy compared to classical approaches, demonstrated the suitability of the proposed model. More applications of the ANNs for this objective can be found in many earlier studies [114-116].

It is well accepted that diverse optimization theories and algorithms can overcome the difficulties that come up with intricate problems [89; 117-127]. Genetic algorithm (GA) is a popular optimization method which was applied by Hamrouni et al. [128] for probabilistic analysis of seismic BC. Saha et

al. [129] presented a solution to the ultimate BC problem using symbiosis organisms search. Confirmed by numerical analysis (in the PLAXIS environment), the acceptability of the proposed method was shown for future applications. Jin et al. [130] could accurately study the ultimate BC and critical slip surface of a rough embedded foundation placed on sands using improved radial movement optimization (IRMO). The efficiency of biogeography-based optimization algorithm (BBO), evolution strategy (ES), and differential algorithm (DE) was investigated by Kashani et al. [131] for the optimal design of the foundation. Gandomi and Kashani [132] professed the superiority of teaching-learning-based optimization algorithm (TLBO) over various swarm-based strategies, such as accelerated PSO, WOA, MFO, for the economical design of shallow foundations.

Moayedi et al. [133] compared two highly popular optimizers of imperialist competition algorithm (ICA) and particle swarm optimization (PSO) for enhancing the performance of the ANN applied to bearing capacity estimation of shallow circular footing. The outputs of the ANNs developed by the PSO and ICA achieved the R² values of 0.9575 and 0.9467, respectively. Therefore, they concluded the excellence of the PSO-ANN model. A comparison between four metaheuristic strategies of ant colony optimization (ACO), league champion optimization (LCA), whale optimization algorithm (WOA), and moth–flame optimization (MFO) incorporated with ANN in forecasting the stability/failure of a soil-footing system was conducted by Moayedi et al. [134]. Respective accuracies of 94.4, 93.5, 93.9, and 93.9% showed the larger optimization competency of the ACO algorithm.

The literature addresses the wide application of metaheuristic algorithms in the BC calculation [135; 136]. It has been well concluded that these algorithms can efficiently deal with providing optimal solutions, due to their global search capability. Based on the findings of earlier studies concerning the successful use of newly-designed techniques, this study uses water cycle algorithm (WCA) for training an ANN in the BC analysis. The WCA is a robust search strategy that has been broadly employed for different applications [137; 138]. Moreover, the competency of this model is checked by two benchmark techniques, namely electromagnetic field optimization (EFO) and shuffled complex evolution (SCE) which are known as relatively quicker algorithms. This strategy, i.e., utilizing automatic error minimization techniques as the trainer of ANN, has been regarded as a promising solution for complex engineering issues.

2 Methodology

2.1 The WCA technique

Most metaheuristic algorithms are nature-inspired, meaning that the main idea is elicited from the natural phenomena or the behavior of creatures. The WCA, as is implied by the name, mimicks the way rivers and streams end up with the sea [139]. Melted snow and glaciers flow downhill to form a stream (or a river). Their water is evaporated, becomes clouds, and returns to the earth [140].

The steps required for implementing the WCA can be explained as follows:

- Step1: Setting the parameters of the algorithm including K_{sr} , K_{pop} , d_{max} , It_{max} .
- Step1: Scattering the initial population and determining sea, streams, and rivers. Assuming K_{pop} as the total size of the population, K_{sr} = 1 + Number of rivers, and K_{streams} (= K_{pop} K_{sr}) as the number of streams, this process is expressed by the below equation:

$$\text{Total population} = \begin{bmatrix} Sea \\ River_1 \\ \vdots \\ Stream_{K_{sr+1}} \\ \vdots \\ Stream_{K_{pop}} \end{bmatrix} = \begin{bmatrix} x_1^1 & x_2^1 & \dots & x_K^1 \\ x_1^2 & x_2^2 & \dots & x_K^2 \\ \vdots & \vdots & \vdots & \vdots \\ x_1^{K_{pop}} & x_2^{K_{pop}} & \dots & x_K^{K_{pop}} \end{bmatrix}$$
(1)

where river, stream, and the sea represent a particular solution by a $1 \times K$ -dimensional array as $[x_1, x_2, ..., x_K]$.

• Step 3: The cost of each member of the existing population is reflected as follows:

$$C_j = Cost_j = f(x_1^j, x_1^j, ..., x_K^j) \qquad j = 1, 2, ..., K_{pop}$$
(2)

• Step 4: Given *NS_k* as the number of streams discharging in the corresponding rivers or the sea, Equation 3 and 4 give the flow intensity of sea and rivers:

$$C_k = Cost_k - CF_{K_{sr+1}}$$
 $k = 1, 2, ..., K_{sr}$ (3)

$$NS_{k} = round \left\{ \left| \frac{C_{k}}{\sum_{k=1}^{K_{sr}} C_{k}} \right| \times K_{streams} \right\}, \quad k = 1, 2, ..., K_{sr}$$

$$\tag{4}$$

• Step 5: Below relationships describe the streams flowing into the sea and rivers:

$$X_{stream}(t+1) = X_{stream}(t) + rand (0, 1) \times G \times (X_{sea}(t) - X_{stream}(t))$$
⁽³⁾

 $X_{stream}(t+1) = X_{stream}(t) + rand (0, 1) \times G \times (X_{river}(t) - X_{stream}(t))$ (6)

where G is a number varying from 1 and 2 (close to 2). Notably, the streams are allowed to move to the rivers from different directions once C > 1.

(5)

• Step 6: The movement of the rivers toward downhill (or the sea) can be formulated as follows:

 $X_{river}(t+1) = X_{river}(t) + rand \times G \times (X_{sea}(t) - X_{river}(t))$ ⁽⁷⁾

- Step 7: The position of a stream that gives a better-fitted solution replaces that of the river.
- Step 8: Likewise, the position of a river which gives a better-fitted solution replaces that of the sea.

• Step 9: Given d_{max} as a very small value for controlling the intensification level, B_U and B_L as the upper and lower bound, respectively, the following procedure checks the conditions of evaporation (for unconstrained problems):

If $|X_{sea} - X_{river}^{j}| < d_{max}$ or rand < 0.1 $j = 1, 2, ..., K_{sr} - 1$ Rain based on Equation 9 End if (8)

$$X_{stream}^{new}(t+1) = B_L + rand \times (B_U - B_L)$$
⁽⁹⁾

As for constrained problems, the WCA uses the below code for enhancing its capability: If $|X_{sea} - X_{stream}^{j}| < d_{max}$ $j = 1, 2, ..., NS_{k}$ Rain based on Equation 11 (10) End if

$$X_{stream}^{new}(t+1) = X_{sea} + \sqrt{\delta} \times randn(1, K)$$
(11)

where *randn* is a random number and δ signifies the variance term showing the searching region in the vicinity of the sea. This is worth noting that for preventing premature convergence in such problems, Equation 10 is only implemented for the streams which have direct movements toward the sea.

• Step 10: The d_{max} is decreased as follows:

$$d_{max}(t+1) = d_{max}(t) - \frac{d_{max}(t)}{It_{max}}$$
(12)

• Step 11: The algorithm is finished if any stopping criterion is met, otherwise it repeats the process from step 5 [141; 142].

2.2 Benchmark optimizer

Electromagnetic field optimization, as the name indicates, is inspired by the electromagnetic behavior of different poles. In this regard, electromagnets with similar/dissimilar poles repel/attract each other. This algorithm was suggested by Abedinpourshotorban et al. [143]. The individuals of the EFO are electromagnetic particles. The goodness of each particle is the basis of classifying them into three groups by the name positive field, negative field, and neutral field. The main idea of this technique for improving the solutions is generating and replacing new particles. More clearly, the generated particle with a better fitness magnitude replaces the worst one. For generating a new individual, one particle is randomly chosen from each one of the triple fields. The position and the pole of the neutral particle are first given to the produced individual. The positive and negative electromagnetics also

affect it (attraction and repulsion process, respectively) [144]. More information about the EFO mechanism can be found in the related literature [145; 146].

Shuffled complex evolution was designed by Duan et al. [147]. This algorithm draws on four major concepts including (i) synthesizing probabilistic and deterministic theories, (ii) performing systematic evolutions on so-called containers "complexes", (iii) doing competitive evolutions, and (4) shuffling the complexes. Scattering the points is the initial step. Considering the function value of the points, they are then sorted in ascending order. Next, the points are partitioned into a number of complexes where each of them can independently evolve and search the viable space. By applying the modified simplex method of Nelder and Mead [148] for global enhancement, some points are chosen from each unit to form a sub-complex. The larger the fitness of the point is, the more the likelihood of generating offspring is. The worst points are replaced by the new offspring [149]. Studies like [150; 151] have explained the SCE in more detail.

3 Data collection

As is known, the settlement (U_y) of a footing is a function of several parameters. In this work, the effect of friction angle (FA), setback distance (SD), elastic modulus (EM), unit weight (UW), dilation angle (DA), applied stress (AS), and Poisson's ratio (PR) is incorporated for measuring the settlement by a series of finite element analysis executed on a two-layered soil system that bears a shallow footing.

Figure 1 depicts the histogram chart of the mentioned parameters. According to the statistical indicators, the values of FA, SD, EM, UW, DA, AS, and PR range in [30, 42], [1, 7] *m*, [17500, 65000] $\frac{kN}{m^2}$, [19.0, 21.1] $\frac{kN}{m^3}$, [3.4, 11.5], [0.0, 1132.6] $\frac{kN}{m}$, and [0.2490, 0.3330]. Also the target parameter (i.e., the U_y) varies from 0 to 0.10 *m*.





Figure 1: Histogram diagram of the parameters of the prepared dataset.

With reference to different conditions for this problem, a total of 901 Uys were recorded for the executed stages. The statistical indicators of mean, standard error, standard deviation, and sample variance are 0.0380, 0.0011, 0.0325, and 0.0011, respectively, for the obtained Uy values. After writing the settlements in front of the corresponding input parameters, the data were permuted randomly and 721 samples (around 80% of records) were selected for exploring the Uy behavior.

4 Results and discussion

This research is an effort to find an appropriate novel trainer of ANN in examining the bearing capacity of a shallow foundation. To achieve this, a hybrid of WCA and MLP is created and applied to predict the settlement of the foundation. The quality of the prediction is addressed by using three accuracy indicators of Pearson correlation coefficient (R), mean absolute error (MAE), and root mean square error (RMSE). Given $U_{y \, i_{predicted}}$ and $U_{y \, i_{expected}}$ as the simulated and real U_{ys} , respectively, Equations 13 to 15 formulate the R, MAE, and RMSE.

$$R = \frac{\sum_{i=1}^{G} (U_{y i_{predicted}} - \overline{U_{y}}_{predicted}) (U_{y i_{expected}} - \overline{U_{y}}_{expected})}{\sqrt{\sum_{i=1}^{G} (U_{y i_{predicted}} - \overline{U_{y}}_{predicted})^{2}} \sqrt{\sum_{i=1}^{G} (U_{y i_{expected}} - \overline{U_{y}}_{expected})^{2}}$$
(13)

$$MAE = \frac{1}{G} \sum_{i=1}^{G} |U_{y_{i_{expected}}} - U_{y_{i_{predicted}}}|$$
(14)

$$RMSE = \sqrt{\frac{1}{G} \sum_{i=1}^{G} \left[\left(U_{y \, i_{\text{expected}}} - U_{y \, i_{\text{predicted}}} \right) \right]^2} \tag{15}$$

4.1 WCA-MLP results

The implementation of any neuro-metaheuristic model consists of several steps. The WCA-MLP is first created by assigning the WCA as the trainer of an MLP network with a $7 \times 7 \times 1$ architecture. As explained, initializing the parameters of the algorithm is the first step. Based on a trial and error process, d_{max} and K_{sr} were set to be 1e-16 and 4, respectively. Also, examining the convergence behavior of the WCA indicated the suitability of 1000 for the maximum number of iterations. The population size (N_{pop}) is another effective factor that was optimized by testing nine values. The convergence curves of the tested models are shown in Figure 2. In this figure, the objective function (on the *y*-axis) is the RMSE of the training data.



Figure 2: The sensitivity of the WCA performance to the population size.

This practice revealed that the best results are yielded by the WCA-MLP with $N_{pop} = 400$. The corresponding RMSE was 0.013677. This value, as well as the MAE = 0.0094281, indicates an acceptable level of accuracy in understanding the U_y behavior. As for predicting this pattern, the RMSE and MAE were 0.015175 and 0.010515, respectively.

As is shown in Figure 3, the correlation for both phases is around 90% which implies a good agreement between the expected and modeled U_y s. The R indices were exactly 0.90527 and 0.89365 for the training and testing samples.



Figure 3: The regression charts of the (a) training and (b) testing results for the WCA-MLP.

4.2 Benchmark results

The EFO-MLP and SCE-MLP were developed in the same way and predicted the U_y . The convergence curves of these models are illustrated in Figure 4. As is seen, the EFO required 5000 iterations to reach a stable convergence during training the MLP. Note that, the N_{pop} s for the EFO and SCE were 25 and 10 determined by a trial and error practice.



Figure 4: The convergence curves of the benchmark methods.

According to the training results, these methods could satisfactorily analyze the relationship between this parameter and related factors. The RMSEs for these two models were close (i.e., 0.014476 and

0.014209). Likewise, the MAEs of 0.010383 and 0.010042 indicated a similar level of accuracy for both models in training the ANN. In the testing phase, the RMSEs of 0.015455 and 0.015484 along with the MAEs of 0.011104 and 0.010976 proved that the used models can present a reliable prediction of the intended parameter.

Figure 5 depicts the regression charts of these models. The R values of 0.89331 and 0.89743 are obtained for the training data and 0.88973 and 0.89001 are obtained for the testing data of the EFO-MLP and SCE-MLP models. These results demonstrate that the produced U_y s are well correlated with the expected values.





(b)



Figure 5: The regression charts of the training and testing results for the (a and b) EFO-MLP and (c and d) SCE-MLP.

4.3 Comparison

From two previous sections, it can be derived that all three metaheuristic algorithms (WCA, EFO, and SCE) could act as a capable trainer for the MLP neural network. In this section, the performance of the proposed algorithm is compared with benchmark ones.

Figure 6 shows graphical views of the training and testing errors calculated for the outputs of the used models. It can be seen that the errors obtained from the WCA-optimized model are more aggregated near the ideal line (Error = 0).







(b)

Figure 6: A graphical comparison of the (a) training and (b) testing errors for all used models.

Moreover, in terms of all accuracy indicators, the prediction of the WCA-MLP was more accurate than EFO-MLP and SCE-MLP. For example, examining the training RMSEs showed that the error of the EFO-MLP and SCE-MLP is 5.84 and 3.89% larger than WCA-MLP (relative to the WCA-MLP). These values were 1.85 and 2.04% for the testing data. Considering the role of the metaheuristic algorithms in combination with the neural system, it is deduced that the MLP configuration designed by the WCA performs more reliably than the other two search strategies. The time taken by the used algorithms for finding the optimal responses is considered, too. While the WCA trained the ANN in 4807.8 seconds, the EFO and SCE needed around 48.9 and 546.5 seconds. Notably, the system used for executing the algorithms was a personal computer with the CPU of Intel core i7 with 16 gigs of RAM). Concerning the reasons for these distinctions, apart from the essence of searching strategies, the benchmark models were implemented with simpler configurations (i.e., smaller N_{pop} s).

4.4 The formula of the WCA-MLP

In this section, the explicit formula of the WCA-MLP is exhibited as a series of linear/non-linear relationships. Figure 7 shows the architecture of the MLP neural network used for approximating the U_y from FA, SD, EM, UW, DA, AS, and PR.



Figure 7: The neural structure of the used predictive model.

The U_y is calculated as follows:

 $U_y = -0.023666 \times HO_1 + 0.901186 \times HO_2 - 0.643029 \times HO_3 + 0.945461 \times HO_4 - 0.716870$ × HO₅ - 0.788679 × HO₆ - 0.104387 × HO₇ + 0.465768 (16)

where

$$HO_i = \frac{2}{1 + e^{-2 \times s_i}} - 1 \tag{17}$$

in which

$$s_{1} = 1.084288 \times FA + 0.595115 \times DA + 0.291941 \times UW + 1.247339 \times EM + 0.391523 \times \\ PR - 0.138593 \times SD - 0.272225 \times AS - 1.848657 \\ s_{2} = -0.249199 \times FA - 0.755865 \times DA - 0.986040 \times UW - 0.972855 \times EM - 0.144769 \times \\ PR + 0.130731 \times SD + 0.909577 \times AS + 1.232438 \\ s_{3} = 1.023457 \times FA - 0.043397 \times DA + 0.855424 \times UW + 0.984439 \times EM + 0.515326 \times \\ PR - 0.177398 \times SD - 0.608510 \times AS - 0.616219 \\ s_{4} = -0.158531 \times FA - 0.271860 \times DA - 1.049325 \times UW - 1.325108 \times EM + 0.375280 \times \\ PR - 0.145215 \times SD - 0.547336 \times AS + 0.000000 \\ s_{5} = -0.607473 \times FA - 0.701226 \times DA - 1.026808 \times UW - 0.867166 \times EM - 0.420470 \times \\ PR - 0.103031 \times SD - 0.750380 \times AS - 0.616219 \\ s_{6} = 0.773196 \times FA + 0.180922 \times DA - 1.280874 \times UW + 0.700894 \times EM - 0.298608 \times \\ PR + 0.712766 \times SD - 0.240574 \times AS + 1.232438 \\ s_{7} = -0.051134 \times FA + 0.712179 \times DA + 0.311052 \times UW - 0.103681 \times EM - 0.963517 \times \\ PR + 1.000864 \times SD - 0.932803 \times AS - 1.848657 \end{aligned}$$

The numbers used in the above equations represent the weights and biases of the MLP optimally found by the WCA during minimizing the learning error. Equation 16 releases the U_y by doing a linear computation on hidden outputs (HO_i). As Equation 17 denotes, calculating HO_1 , HO_2 , ..., and HO_7 consists in obtaining s_1 , s_2 , ..., and s_7 from Equations 18 to 24, respectively. In fact, Equation 17 represents a so-called activation function "Tansig" that is used for the neurons in the hidden layer. According to many previous studies, Tansig is a suitable function that can nicely deal with abrupt changes in the dataset [152; 153].

5 Conclusions

The methods based on neural computing have been popularly used for bearing capacity analysis. In this work, the water cycle algorithm, electromagnetic field optimization, and shuffled complex evolution algorithms were appointed for training an MLP neural network in approximating the settlement of a shallow foundation. The main conclusions are as follows:

• Implementing the models by their optimal parameters results in a higher quality of training.

- Compared to the EFO and SCE, the WCA needs a considerably larger population for accomplishing the optimization (*N_{pop}s* of 400 vs. 25 and 10). Also, the EFO was implemented 5000 times to reach a stable situation.
- Based on more than 88% correlation of the outputs in all stages, the used hybrid models can properly capture and reproduce the U_y behavior.
- The WCA-MLP surpassed the other two models in terms of all RMSE, MAE, and R accuracy indicators. In other words, the searching strategy of this algorithm could find a more promising solution to the given problem (i.e., setting the appropriate configuration of the MLP).
- The tested WCA-ANN can be used for accurate analysis of the U_y in practice.

Conflict of interest:

Authors declare no conflict of interest.

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Figures



Figure 1

Histogram diagram of the parameters of the prepared dataset.



Figure 2

The sensitivity of the WCA performance to the population size.



Figure 3

The regression charts of the (a) training and (b) testing results for the WCA-MLP.



Figure 4

The convergence curves of the benchmark methods.





(b)



Figure 5

The regression charts of the training and testing results for the (a and b) EFO-MLP and (c and d) SCE-MLP.



(a)



Figure 6

A graphical comparison of the (a) training and (b) testing errors for all used models.





The neural structure of the used predictive model.