Civil Engineering Beyond Limits 2 (2025) 1995

Civil Engineering Beyond Limits

journal home: www.acapublishing.com/journals/1/cebel

Research Article

# Application of Heuristic Optimization Approaches to Evaluate Compaction Parameters

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**Keywords**

*Optimal moisture content,*
*Machine learning,*
*Maximum dry density,*
*Meta-heuristic optimization,*
*Genetic algorithm.*

**Abstract**

In geotechnical engineering and construction, the optimal moisture content (OMC) and maximum dry density (MDD) is crucial for determining the ideal conditions for soil strength and stability in infrastructure. Traditional laboratory techniques for calculating OMC and MDD are both costly and time-consuming. Machine learning offers a potential alternative for traditional empirical approaches by making it easier to create complex prediction models and algorithms that can improve the accuracy and efficacy of forecasts of compaction parameters. Machine learning-specifically Meta-heuristic optimization (MHO)-approaches are high-level problem-solving strategies that seek optimal or near-optimal solutions to difficult optimization problems, which are frequently non-linear, multi-modal, or non-differentiable. The Genetic Algorithm (GA), Generalized Population-Based Adaptive Search (GPAS), and Particle Swarm Optimization (PSO) are three powerful meta-heuristic optimization algorithms that are commonly employed to solve complex optimization issues. The goal of this project is to develop a framework that uses meta-heuristic optimization techniques to estimate OMC and MDD. Using MHO models, the study shows a substantial correlation between OMC and MDD, respectively, with significant soil factors such as specific gravity, Atterberg limits, and grain size distribution parameters. This study depicts three distinct models for the prediction of OMC and MDD named GA, PSO, and GPAS models. Among the models, the GA model demonstrated the highest accuracy in predicting OMC ($R^2$ = 0.9999, MSE = 0.0001), while the PSO model was most effective for MDD prediction ($R^2$ = 0.9660, MSE = 0.1871). These findings highlight the accuracy and dependability of the GA technique, which presents a viable method for precisely forecasting the MDD and OMC of soil stabilization mixtures in a range of engineering applications. Additionally, it reduces the negative effects that soil extraction and modification have on the environment.

## 1. Introduction

Every construction that rests on the ground needs to be stable and safe. It is necessary to identify the properties of the soil in order to meet these safety and stability standards. MDD and OMC are important factors in soil compaction and geotechnical engineering because they influence soil structure durability, strength, and longevity [1]. Determining MDD and OMC by laboratory methods is a laborious and time-consuming process. As a result, several scientists, researchers, and investigators created and implemented various techniques and approaches to calculate the soil's compaction characteristics [2-3]. Several scholars developed empirical correlations as a faster and easier way to determine the compaction properties of soils [3-5]. However, the empirical equations contain a substantial error obtained from both linear and multilinear regression [6-7]. Several researchers have recently implemented machine learning and deep learning to precisely analyze the compaction parameters due to the growing advancements in artificial intelligence technology. ML is used in predicting compaction characteristics and evaluating different geo-hazards [8-9]. Hasnat et al. (2019) [10] used Support Vector Machines (SVM) to create a model for predicting soil compaction characteristics. For the optimal moisture content and maximum dry density, the best R-squared values obtained

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Received 18 Apr 2025; Revised 29 Apr 2025; Accepted 29 Apr 2025 https://doi.org/10.36937/cebel.2025.1995

from the projected equation are 0.86 and 0.91, respectively. Jalal et al. (2021) [11] created new empirical GP-based prediction models to assess the compaction characteristics of expansive soils. The study discovered that the produced models performed better when the suggested models were contrasted with earlier empirical models. Sinha et al. (2008) [12] established a prediction model for soil permeability and compaction characteristics using artificial neural networks (ANNs). Abidhan et al. (2023) [13] used a hybrid intelligence model that included an artificial neural network (ANN) and a grey wolf optimizer (GWO) to monitor soil compaction in civil engineering projects. The study contrasted the outcomes of the created models with those of four other hybrid ANNs that were constructed using the salp swarm algorithm, Harris Hawks optimization, slime mold algorithm, and particle swarm optimization. The ANN-GWO provides the most accurate estimation for OMC (RMSE = 0.0986, $R^2$ = 0.7273) and MDD (RMSE = 0.1017, $R^2$ = 0.7147) of soils, according to the testing dataset's results. Using 212 data, Ardakani et al. (2017) [14] predicted soil compaction parameters using a GMDH-type neural network and a genetic algorithm. They showed that the GMDH-type NN is very good at predicting MDD (Testing: R=0.93 and RMSE=0.63) and OMC (Testing: R=0.96 and RMSE=1.79). Another study, which developed ANN models using 180 laboratory test compaction data, found that the OMC and MDD models of ANN performed 0.91 and 0.92, respectively [15].

Machine learning (ML) is an essential part of artificial intelligence. However, other research employed machine learning (namely SVM, RF, LSTM, and ANN) with several optimization techniques to predict MDD and OMC as mentioned. This study aims to address the limitations of past research by investigating the application of three meta-heuristic optimization techniques (GA, GPAS, and PSO) to develop accurate and efficient models for predicting MDD and OMC. The performance of these models will be compared, and their potential to improve geotechnical engineering practice will be evaluated. These approaches may reduce the risk of getting trapped in local optima, as they may optimize the solution space globally. In addition, metaheuristics are reliable for practical engineering applications since they offer adaptability and flexibility in a variety of soil conditions and they can also enhance the performance of machine learning models by modifying the hyperparameters or enhancing the model architecture. Ultimately, using metaheuristic optimization to forecast OMC and MDD not only enhances model performance but also helps geotechnical engineers make better informed, economical, and efficient decisions. To create the prediction models, soil test data from laboratory experiments were employed, as indicated in the section below.

## 2. Materials and Methods

The whole dataset consists of laboratory test results for a variety of soil index parameters that were gathered from a private organization. The following information is included in the dataset: Specific Gravity (Sp. Gr.), MDD, OMC, Sand (%), Silt (%), Clay (%), Liquid Limit (LL), Plastic Limit (PL), Plasticity Index (PI), and Fineness Content (%). Table 1 represents the statistical parameters of the input dataset where mean, standard deviation (std), minimum (min) and maximum (max) value of each input are presented.

Table 1. Statistical Parameters for Input data

| Parameters | Count | Mean | Standard deviation | Minimum value | Maximum value |
|---|---|---|---|---|---|
| LL | 300 | 26.5093 | 5.09056 | 20.15 | 38 |
| PL | 300 | 16.7968 | 4.62768 | 10.57 | 25 |
| PI | 300 | 9.7125 | 1.57121 | 6.12 | 14 |
| sand % | 300 | 12.487 | 9.89261 | 2 | 60.04 |
| Silt % | 300 | 72.6988 | 8.78998 | 34.35 | 87.4 |
| Clay % | 300 | 14.827 | 6.09376 | 5.61 | 26 |
| FC (%) | 300 | 23.7755 | 7.43475 | 12.52 | 63.62 |
| Specific gravity | 300 | 2.69263 | 0.08873 | 2.5 | 2.79 |
| MDD | 300 | 15.2656 | 1.38923 | 9.2214 | 17.9523 |
| OMC | 300 | 23.7755 | 7.43475 | 12.52 | 63.62 |

Figures 1 and 2 show the results of the Pearson correlation analysis, which offers a thorough grasp of the connections between the soil characteristics used in this investigation.

| | LL | PL | PI | Sand % | Silt % | Clay % | FC (%) | Sp. Gravity | MDD |
|---|---|---|---|---|---|---|---|---|---|
| LL | 1 | | | | | | | | |
| PL | 0.95215 | 1 | | | | | | | |
| PI | 0.43553 | 0.13957 | 1 | | | | | | |
| Sand % | -0.2893 | -0.3930 | 0.2202 | 1 | | | | | |
| Silt % | -0.3205 | -0.2251 | -0.3754 | -0.7929 | 1 | | | | |
| Clay % | 0.9318 | 0.9624 | 0.1843 | -0.4763 | -0.1578 | 1 | | | |
| FC (%) | 0.1500 | 0.0391 | 0.3708 | 0.1945 | -0.2503 | 0.0450 | 1 | | |
| Sp. Gravity | 0.4497 | 0.5465 | -0.1525 | -0.3949 | 0.0919 | 0.5091 | -0.2851 | 1 | |
| Dry Density | -0.2620 | -0.1544 | -0.3941 | -0.2807 | 0.4108 | -0.1371 | -0.9186 | 0.1579 | 1 |

Figure 1. Pearson correlation matrix for MDD

Moreover, it measures the correlation between changes in one variable and changes in another. With a value of +1 denoting a perfect positive linear correlation, a value of -1 denoting a perfect negative linear correlation, and 0 denoting no linear correlation between the variables, the coefficient falls between -1 and +1.

| | LL | PL | PI | sand % | Silt % | Clay % | FC (%) | Sp. Gravity | OMC |
|---|---|---|---|---|---|---|---|---|---|
| LL | 1 | | | | | | | | |
| PL | 0.9521 | 1 | | | | | | | |
| PI | 0.4355 | 0.1395 | 1 | | | | | | |
| sand % | -0.2893 | -0.393 | 0.2202 | 1 | | | | | |
| Silt % | -0.3205 | -0.2251 | -0.3754 | -0.792 | 1 | | | | |
| Clay % | 0.9318 | 0.9624 | 0.1843 | -0.476 | -0.1578 | 1 | | | |
| FC (%) | 0.1500 | 0.0391 | 0.3708 | 0.1945 | -0.2503 | 0.0450 | 1 | | |
| Sp. Gravity | 0.4497 | 0.5465 | -0.1525 | -0.3949 | 0.0919 | 0.5090 | -0.285 | 1 | |
| OMC | 0.1500 | 0.0391 | 0.3708 | 0.1945 | -0.250 | 0.0450 | 0.9970 | -0.2851 | 1 |

Figure 2. Pearson correlation matrix for OMC

LL and PL have a very high correlation (r = 0.952), which confirms their intrinsic relationship as crucial consistency metrics. Both are highly influenced by clay content (r = 0.932 and 0.962, respectively). Expected trends are revealed by particle size distribution analysis, which shows that the sand content has a strong inverse relationship with silt content (r = -0.793) and negative correlations with plasticity parameters (LL, PL) and clay percentage. This indicates that the granular fractions in the soil composition are complementary. Particularly noteworthy are the moisture-related correlations, where Field Capacity (FC%) shows an almost perfect positive linear relationship with Natural Moisture Content (r = 0.997), indicating that FC% essentially determines the in-situ water retention capacity. The strong negative correlation between FC% and dry density (r = -0.919) provides crucial engineering insight, demonstrating that soils with higher water-holding capacity tend to have lower dry densities, which has significant implications for compaction characteristics and bearing capacity assessments. Specific gravity displays moderate positive correlations with plasticity parameters (LL, PL) and clay content, likely attributable to the higher density of clay minerals compared to coarser particles. These intricate association patterns not only improve our basic comprehension of the relationships between soil properties, but they also offer a solid scientific foundation for creating geotechnical engineering prediction models, especially to estimate compaction behavior.

To achieve the research objective, gathered data was utilized to forecast MDD and OMC based on selected algorithms. To reduce the complexity of running the models, data pretreatment like data cleaning and dimensionality reduction was performed. Data cleaning process is so performed to find any nill or null or not applicable values on the dataset. For this study, there were no nill/null or not applicable values. This treatment is done to find better models, faster computation, more reliable insights. After loading and preprocessing the dataset, StandardScaler (handles outliers better than minmaxscaler) is used to scale the features, and the dataset is divided into training (80%) and testing (20%) sets to provide the model enough data to learn and enough data to test. Figure 3 depicts the methodology for this study.

The GA creates a population of individuals, each representing a distinct collection of hyperparameters, including the MLP Regressor's maximum iterations, regularization parameter (alpha), learning rate, activation function, and hidden layer size and number. In order to accommodate the minimization framework, the $r^2$ score is negated since PSO minimizes the objective function. For every hyperparameter, the search is limited within predetermined parameters (maximum iterations, regularization parameter, learning rate, activation function, and hidden layer size and number etc.), and PSO iterates over a swarm of particles to find the best combination. In order to balance exploration (global search) with exploitation (local refinement), GPAS generalizes and modifies important techniques that are inspired by population-based metaheuristics such as GA, PSO, and Differential Evolution (DE). In the case of GPAS, it focuses on minimizing the mean squared error (MSE) through cross-validation. The GPAS class initializes particles of population, each of which represents a possible solution (hyperparameter set) with arbitrary positions and velocities inside a certain search space. The objective function, which trains an MLPRegressor with the given hyper parameters (hidden layer size and learning rate) and calculates the mean squared error (MSE) through 5-fold cross-validation, is used to assess each particle's fitness. The algorithm keeps track of each particle's individual best scores and placements in addition to the global best solution for all particles. Selection, crossover, and mutation are examples of leveraging evolutionary operations that were used to iteratively improve model performance through the optimization of hyperparameters. Table 2 represents the hyperparameters used for each model. After finding the best parameters, the target values are so detected using the developed model by these best hyperparameters.

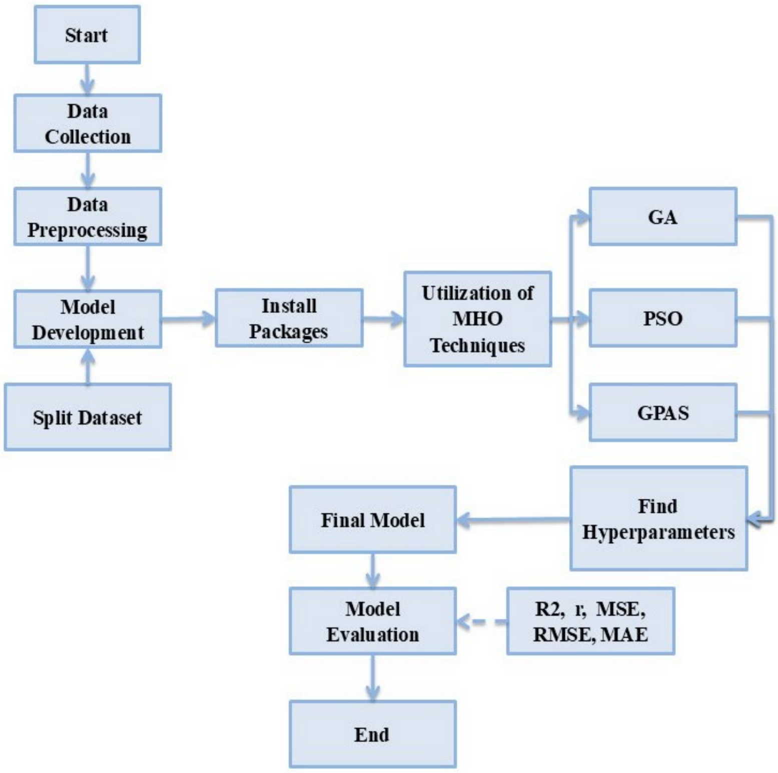


Figure 3. Research methodology

Table 2. Hyperparameters used for each model

| Model | Parameters | MDD | OMC |
|---|---|---|---|
| GA | Activation | identity | identity |
| | Hidden Layer Sizes | 66 | 87 |
| | Learning Rate | 0.08564 | 0.07055 |
| | Max Iterations | 95 | 700 |
| PSO | Hidden Layer Sizes | 10 | 79 |
| | Learning Rate | 0.03104 | 0.06318 |
| | Alpha | 0.44237 | Not Applicable |
| | Packages | pyswarm | pyswarm |
| | Max Iterations | 1000 | 500 |
| GPAS | Hidden Layer Sizes | 500 | 5 |
| | Learning Rate | 0.00138 | 0.09219 |
| | Max Iterations | 500 | 500 |

## 3. Results and Discussion

OMC and MDD are two crucial factors in soil compaction engineering, can be predicted with machine learning algorithms. Complex correlations between compaction parameters and soil qualities (such as particle size distribution and plasticity index) can be efficiently analyzed using meta-heuristic techniques. In this study, the GA, PSO, and GPAS algorithms were successfully used to optimize the parameters of machine learning models in order to enhance their performance. Model performance was evaluated using statistical indicators such as $R^2$ i.e. The percentage that the independent variables account for in explaining the variance in the dependent variable, Pearson correlation coefficient (r) i.e. shows the linear relationship's direction and strength among the variables, mean absolute error (MAE) i.e. the mean absolute variation between expected and actual values, providing a clear indication of the error magnitude, mean squared error (MSE) i.e. calculates the average squared errors, and root mean squared error (RMSE) i.e. provides a measure of prediction accuracy. These metrics evaluate predictive performance, accuracy, and model fit collectively. The particular application and data variability determine the acceptable conditions for model evaluation metrics like $R^2$, R, MSE, RMSE, and MAE. A robust model fit is often indicated by an $R^2$ value above 0.8, and a high linear correlation between predicted and observed values is suggested by r value above 0.9 [16]. Better performance is indicated by lower values for error-based metrics; RMSE and MAE should ideally be within 10–30% of the range of the target variable [17]. Whereas MAE offers a more impartial assessment of overall correctness, RMSE is more susceptible to significant errors. MSE should be kept to a minimum, even when squared units make it harder to read [18].

As the statistical parameters satisfy the optimal suggestion for the successiveness of machine learning models, the results for predicted MDD, shown in Table 3, demonstrate that each model can predict MDD. The best performance is obtained at testing ($R^2$=0.9751; r=0.9881; MAE=0.2387; MSE=0.0977; RMSE=0.3127), training ($R^2$=0.9569; r=0.926; MAE=0.3459; MSE=0.0977; RMSE=0.3127), and overall data ($R^2$=0.9660; r=0.9503; MAE=0.3362; MSE=0.1871; RMSE=0.4325) for the PSO model to predict MDD.

Table 3. Performance metrics for the prediction of MDD

| Model | | $R^2$ | r | MAE | MSE | RMSE |
|---|---|---|---|---|---|---|
| GA | Test | 0.958 | 0.9794 | 0.3378 | 0.1648 | 0.406 |
| | Train | 0.8107 | 0.9052 | 0.3765 | 0.2564 | 0.5064 |
| | All | 0.8751 | 0.9378 | 0.3688 | 0.2381 | 0.4879 |
| PSO | Test | 0.9751 | 0.9881 | 0.2387 | 0.0977 | 0.3127 |
| | Train | 0.9569 | 0.9260 | 0.3459 | 0.1939 | 0.4404 |
| | All | 0.9660 | 0.9503 | 0.3362 | 0.1871 | 0.4325 |
| GPAS | Test | 0.7928 | 0.9142 | 0.635 | 0.8148 | 0.9026 |
| | Train | 0.9172 | 0.9581 | 0.2459 | 0.1121 | 0.3349 |
| | All | 0.8674 | 0.9357 | 0.3237 | 0.2527 | 0.5027 |

The statistical evaluation parameters depicted in Table 4 show that each model is capable of predicting the OMC optimally with the $r^2$ value of about 0.99. Comparing all statistical parameters, it is found that the GA model is best to predict OMC for test ($R^2$ = 0.9999; r = 0.9999; MAE = 0.0104; MSE = 0.0001; RMSE = 0.0132), train ($R^2$ = 0.9999; r = 0.9999; MAE = 0.008; MSE = 0.0001; RMSE = 0.0109), and overall ($R^2$ = 0.9999; r = 0.9999; MAE = 0.0085; MSE = 0.0001; RMSE = 0.0111) data.

Table 4. Performance metrics for the prediction of OMC

| Model | | $R^2$ | r | MAE | MSE | RMSE |
|---|---|---|---|---|---|---|
| GA | Test | 0.9999 | 0.9999 | 0.0104 | 0.0001 | 0.0132 |
| | Train | 0.9999 | 0.9999 | 0.008 | 0.0001 | 0.0109 |
| | All | 0.9999 | 0.9999 | 0.0085 | 0.0001 | 0.0111 |
| PSO | Test | 0.9945 | 0.9999 | 0.4894 | 0.6979 | 0.8354 |
| | Train | 0.9939 | 0.9988 | 0.3554 | 0.2057 | 0.3554 |
| | All | 0.9944 | 0.9993 | 0.3822 | 0.3042 | 0.5515 |
| GPAS | Test | 0.9993 | 0.9997 | 0.0939 | 0.0824 | 0.2871 |
| | Train | 0.9999 | 0.9999 | 0.0189 | 0.0005 | 0.0229 |
| | All | 0.9996 | 0.9998 | 0.0339 | 0.0169 | 0.1301 |

Figures 4 and 5 illustrate the plot generated by the actual and predicted values of MDD and OMC, respectively, for the developed models.

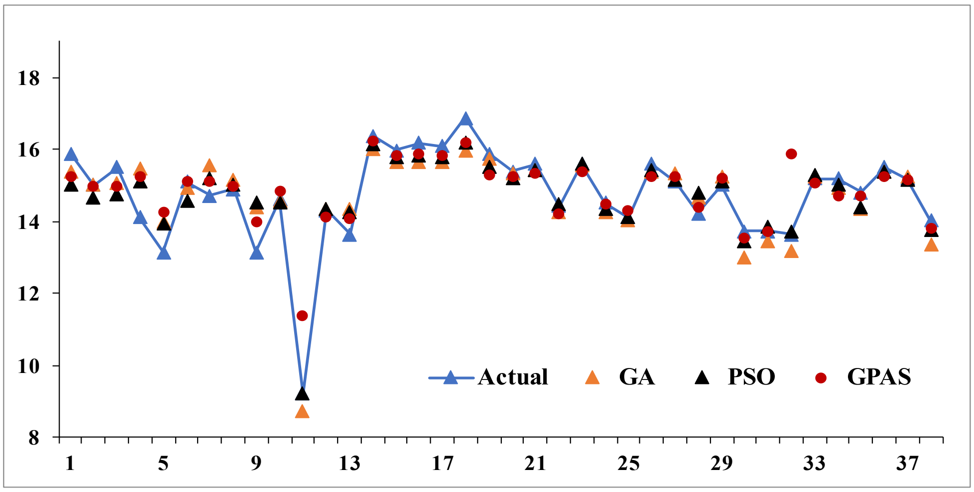


Figure 4. Comparison of Actual vs. Predicted Maximum Dry Density (MDD) Values for GA, PSO, and GPAS Models

The best-developed model, which numerically predicts values about to close to the actual value, is displayed in the comparison plot. Nonetheless, all of the models properly forecast MDD; the GA forecasts value better than PSO and GPAS since the marker for the actual value and the GA-predicted value coincide. The ability of the three established models to predict OMC is shown in Figure 5.

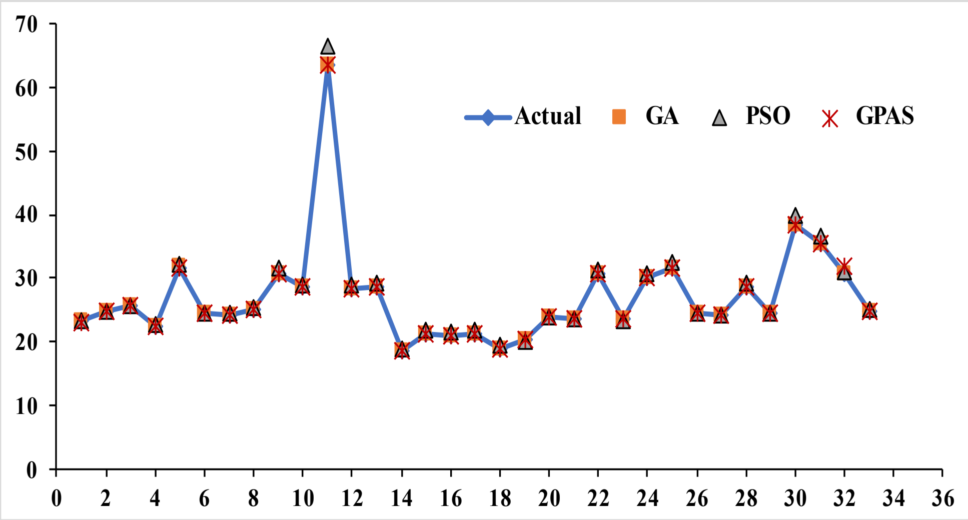


Figure 5. Comparison of Actual vs. Predicted Maximum Dry Density (MDD) Values for GA, PSO, and GPAS Models

Additionally, the models are validated using the performance matrices in Table 5. The values of all the matrices are extremely near to the performance's ideal value. The comparison plot for OMC prediction depicts the markers in the same position without a single dissimilarity, which validates the developed models.

**4. Conclusions**

Machine learning offers various benefits over traditional geotechnical field and laboratory testing methods. Machine learning algorithms may find intricate patterns and connections between soil properties by examining large datasets, which improves forecast accuracy. This article is the first that utilized metaheuristic optimization tools (GA, PSO, and GPAS) to predict MDD and OMC. Based on the values of statistical parameters mentioned earlier, it is evident that the developed models show tremendous results to predict the target variable. When comparison is done among the statistical parameters for each model, it is found that PSO (testing data, $r^2$=0.9751, r=0.9881, MSE=0.0977; training data, $r^2$=0.9569, r=0.9260, MSE=0.1939; overall data, $r^2$=0.9660, r=0.9503, MSE=0.1871) shows the best results to predict MDD, and GA (test data, $r^2$=0.9999, r=0.9999, MSE=0.0001; train data, $r^2$=0.9999, r=0.9999, MSE=0.0001; and overall data, r2=0.9999, r=0.9999, MSE=0.0001) holds the position of the best model for this study to predict OMC. The findings indicate that, compared to experimental results, the accuracy of all suggested models is satisfactory. According to the models' performance measure values, the MHO models for MDD and OMC prediction have outperformed other models that have been published in the literature. The results show that the constructed models are reliable and can be utilized with confidence, and they are corroborated by the results of experimental experiments reported by other researchers. According to this inquiry, PSO and GA are very promising methods that can be used to evaluate the fundamental connections between the various interconnected input and output data for a variety of civil engineering projects where compaction parameters are an important parts. Moreover, these models have several advantages over conventional empirical techniques, such as increased accuracy, less experimental work, and the capacity to handle high-dimensional and non-linear data. By applying machine learning, engineers can enhance soil stability, optimize compaction processes, and general geotechnical construction performance. Although, this study demonstrates a successful machine learning techniques to predict compaction parameters within a short period and of course the method is cost effective over traditional laboratory methods of compaction parameters, further study can increase the validation of such kind of ML methods with more datasets and robust machine learning algorithms.

## Declaration of Conflict of Interests

The authors declare that there is no conflict of interest. They have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

## Authors Contribution

Md. Mahabub Rahman: Supervision, Data curation, writing original draft. Md. Abu Sayed: writing Code, visualization, review and editing. Mst. Mariam Khatun: Methodology, investigation, writing. Afsana Mimi: Performed analysis, review and editing original draft.

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## How to Cite This Article

Rahman, M.M., Sayed, M.A., Khatun, M.M., and Mimi, A., Application of Heuristic Optimization Approaches to Evaluate Compaction Parameters, Civil Engineering Beyond Limits, 2(2025), 1995.
https://doi.org/10.36937/cebel.2025. 1995