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Prediction of Maximum Dry Density of Soil using Genetic Algorithm

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***Abstract*— This paper deals with the application of genetic algorithm for the prediction of maximum dry density of soil. Compaction is the process by which soil is densified by reducing the air voids in it. The degree of compaction required for a given soil is measured in terms of its dry density which is maximum at the optimum moisture content. However this parameter, determined by laboratory compaction requires considerable time and effort. Hence its development from the index properties of soil helps to reduce the effort.. The development and generation of the genetic model was done using a large database containing about 200 case histories from various sources in the Ernakulam district, Kerala. The correlation of the predicted values with the actual values was determined and it was found that genetic algorithms can be used with a high degree of accuracy. The equations thus obtained can be used in the prediction of compaction parameters for new cases.**

***Keywords*— Genetic algorithm; compaction; maximum dry density**

I. INTRODUCTION

Soil compaction is the process in which an external compactive effort applied to the soil causes its densification. Compaction increases soil density, thereby increasing its shear strength, stability and load bearing capacity. The degree of compaction required is measured in terms of the dry density of soil which is maximum at the optimum moisture. The soil type, its grain size distribution, index properties and specific gravity greatly influences the maximum dry density (MDD). Procator compaction test is the most commonly used test to determine the maximum dry density of soil. But they can be quite costly, laborious and time consuming. However determination of the index properties of soil is relatively simple and inexpensive. In this research work, an attempt has been made to predict the maximum dry density of soils in terms of its index properties with the help of a genetic algorithm approach.

II. GENETIC ALGORITHM

A genetic algorithm is a search algorithm inspired by the evolutionary mechanisms like selection, crossover and mutation to search for functions that will best fit the set of experimental data. The genetic algorithm procedure is as shown in Fig. 1.

The database for the development of the genetic model consists of 200 laboratory test cases from various soil testing laboratories in Ernakulam, Kerala. The database mainly consist of c-Φ soils. The model inputs are Liquid limit (W_L), Plastic limit (W_P), Percentage fines (f), Percentage sand (s), Percentage gravel (g) and Specific gravity (G). These inputs were used to predict the MDD of soil.

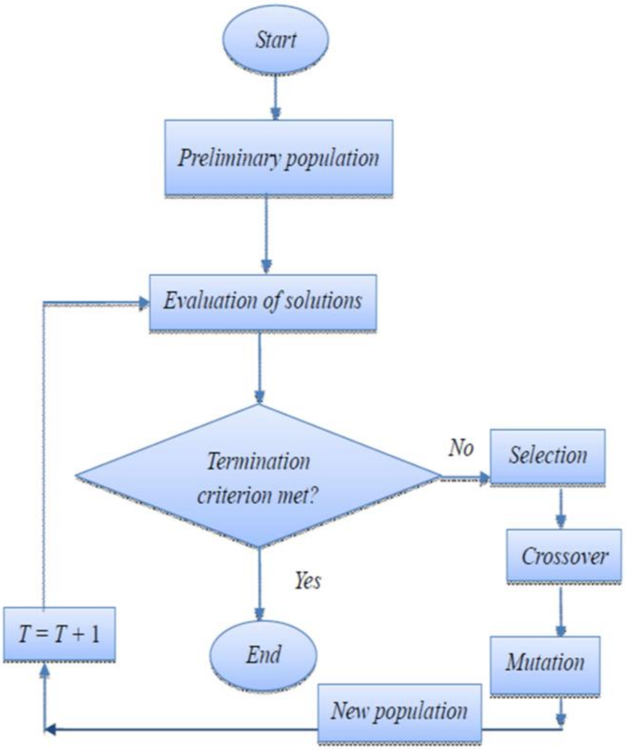

Fig. 1. Genetic Algorithm Procedure

A. Data Division

The data is randomly divided into training and testing datasets by using a statistically consistent approach. Statistically consistent approach ensures that the statistical parameters (mean and standard deviation) of both the datasets are almost the same and hence represent the same statistical population. However there may be still some minor differences in the statistical parameters of the training and testing datasets since the data contains events that cannot be repeated everywhere in the data set. 165 cases (82.5%) of the data were used for training the model and the remaining 35 cases (17.5%) were used for testing the performance of the model. The mean and standard deviation of the training and testing datasets are summarized in Table 1.

Table 1. Statistical Parameters of the data sets

Model Input	Statistical Parameter	Training set	Testing set
Liquid Limit	Mean	50.5636	47.6857
	Standard Deviation	10.5497	13.8134
Plastic Limit	Mean	29.5393	29.6000
	Standard Deviation	7.7076	9.0560
Percentage fines	Mean	36.5151	39.3428
	Standard Deviation	16.6666	16.4029
Percentage fines	Mean	41.9627	45.912
	Standard Deviation	16.2637	19.5437
Percentage fines	Mean	21.5826	24.74514
	Standard Deviation	16.6209	18.0394
Specific gravity	Mean	2.6156	2.6557
	Standard Deviation	0.0778	0.1077
Maximum Dry Density	Mean	1.5859	1.5492
	Standard Deviation	0.1711	0.1719

III. FORMULATION OF THE GENETIC MODEL

A. *Preliminary Population*

Each chromosome in the genetic model contains a variable array and an operator array. The variable array contains the co-efficient and power terms of the six input variables. The coefficient variables were assigned a random value between 0 and 500 and the power terms were assigned a random value between -3 and +3. The operator array consists eleven slots, six of them for placing the input variables and the remaining five slots for placing the arithmetic operators connecting the variable terms. An initial population of 1000 chromosomes were used for the development of the model. The operator type and its position were randomly generated. Post fixing was then done to generate 1000 random equations for predicting the MDD.

B. *Evaluation of Solutions*

The input variables of the training dataset were substituted in the randomly generated equations to obtain MDD. A comparison between the predicted MDD and the actual MDD was then done to determine the error in the prediction of MDD. For all the randomly generated equations of MDD, the sum of squares of all the data in the training dataset was calculated.

C. *Selection*

In the selection process, only those randomly generated equations having lower fitness values are carried forward to the next generation whereas the others die out. Out of the different methods available, the Roulette wheel method was adopted.

D. *Crossover*

Half of the initial population was carried to the next generation. While the remaining half were obtained by crossover between any two randomly selected parents. Crossover probability is generally fixed in the range of 0.7 to 0.8. A typical crossover process is shown in Fig. 2.

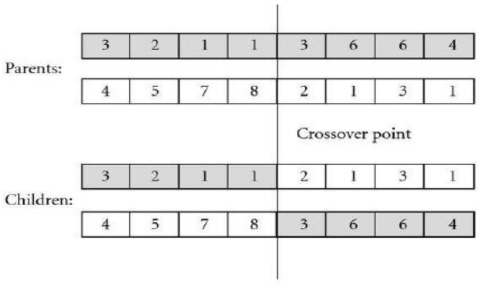

Fig. 2. A typical crossover operation

E. *Mutation*

Mutation is a process in which a random number in the variable array is replaced by another random number or the type and position of the operators in the operator array is replaced by another. Mutation allows the program to search for a better solution in areas outside the local optimum. A typical mutation process is shown in Fig. 3.

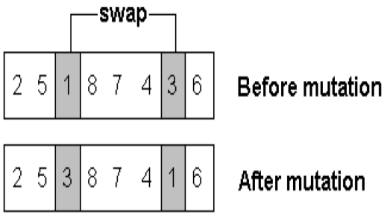

Fig. 3. A typical mutation operation

F. *Number of generations*

A single generation comprises of generation of an initial population, selection, crossover and mutation. The selected population after crossover and mutation enters into the next generation and the entire process of evaluation, selection, crossover and mutation repeats. Hence a higher initial population may result in a more relevant solution. The full algorithm was implemented by coding in Scilab 5.5.2.

IV. RESULTS AND DISCUSSSIONS

The entire program was run several times by changing the mutation and crossover probabilities for the same initial population and number of generations keeping the crossover and mutation probabilities the same. Out of the different solutions obtained, the following solution was found to be the most reliable in the prediction of MDD.

$$MDD = 185.7071 W_L^{-2.6978} + 0.692 W_p^{0.185} + 6.7799 f^{-1.1512} + \frac{86.2882 s^{-2.1669} + 464.2577 g^{0.0217}}{288.0907 G^{2.7598}}$$

Where,

W_L= Liquid limit (%)

W_P = Plastic limit (%)

f = Percentage fines (%)

s = Percentage sand (%)

g = Percentage gravel (%)

G= Specific gravity

The performance of the model was analyzed by using the testing set which was not used for the model development and it has been summarized in Table 2.

Table 2. Performance analysis of model with the actual MDD

Initial Population	Number of generations	Correlation coefficient (R)	RMSE
1000	1000	0.9197	6.7723
1000	500	0.5311	10.6317
1000	100	0.3803	25.6714

The variations of the predicted MDD with the actual MDD for both the training and testing datasets are shown in Fig. 4 and Fig. 5.

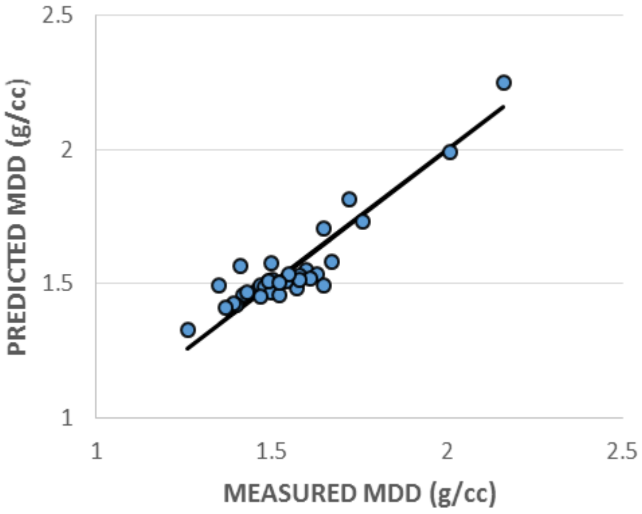

Fig. 4. Performance of the model with testing set for MDD

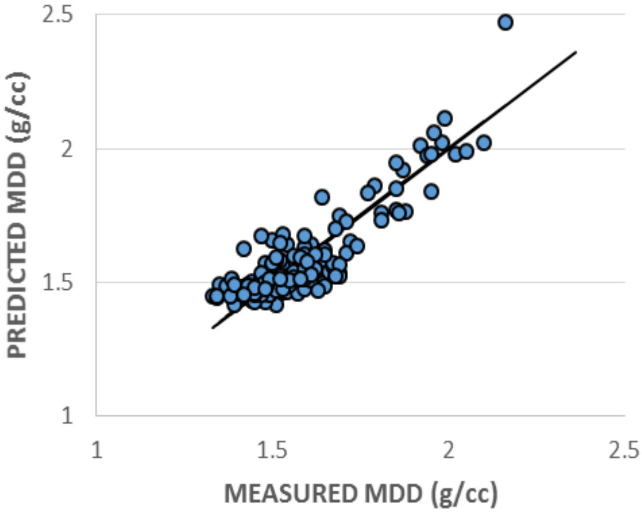

Fig. 5. Performance of the model with training set for MDD

V. CONCLUSION

The prediction of Maximum Dry Density of soils using laboratory techniques is quiet time consuming and laborious. Hence its prediction using the genetic algorithm approach can help reduce the efforts and at the same time give a reliable result. Even though the genetic algorithm has the ability to predict MDD it should be noted that the developed models can be used for only preliminary design phases.

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