

Prediction of Optimum Moisture Content of Soil using Genetic Algorithm

Fasna M..B.^{1,*}, Fathima Zuhara T. N.² and Sowmya V. Krishnankutty³

¹Federal institute of science and technology, Mookkanoor
Kerala, India.

²Federal institute of science and technology, Mookkanoor
Kerala, India.

³Federal institute of science and technology, Mookkanoor
Kerala, India.

*Corresponding author's email: fasnamb123 [AT] gmail.com

ABSTRACT— A genetic model for the prediction of compaction parameter 'Optimum moisture content' is developed in this project. It is difficult to obtain OMC directly from the field, because it needs lot of effort and time by using laboratory method. The development of OMC from index properties of soils helps to reduce this effort. The considered index properties in this project are liquid limit, plastic limit, percentage fines, percentage sands, percentage gravels and specific gravity. The development and verification of the genetic model was done using a large database with 200 case histories from various sources and Geo Technical Engineering Laboratories from Ernakulum district, Kerala. The dataset mainly is of $c-\Phi$ soils. The correlation of predicted data with actual measurements was found out and got to know that the genetic algorithm method have good degree of accuracy.

Keywords— Optimum Moisture Content, Genetic Model, $c-\Phi$ soil, index properties

1. INTRODUCTION

Compaction of soil is defined as a simple ground improvement technique by which the soil particles are artificially packed together by mechanical means in order to decrease its porosity and increases its dry unit weight. This will cause an increase in strength, reduce shrinkage and permeability. It is usually achieved by standard proctor test. One of the important parameters of compaction is Optimum Moisture Content (OMC) and it depends on the index properties of soil. OMC is the water content at which maximum compaction can be achieved. The compaction parameters which are determined from laboratory tests are laborious and time consuming. In this project a model is proposed in order to predict optimum moisture content (OMC) using index properties of soil which are Liquid Limit, Plastic limit, Percentage fines, Percentage sands, Percentage gravels, Specific gravity by genetic algorithm methodology (GA). Using this model, OMC can be easily predicted.

2. LITERATURE REVIEW

Genetic algorithms have been widely used to minimize the error function. It is shown that many problems to the solution arise as the number of unknown parameters increases. Several relationships can be found in the literature to estimate the compaction characteristics of soil based on some geotechnical parameters such as liquid limit (LL), plastic limit (PL), specific gravity (G), compaction energy (E), grain size distribution and soil classifications. Johnson and Sallberg (1962) made an attempt to predict the compaction parameters by developing a chart, which is a plot between plastic limit and liquid limit, and accordingly different zones of optimum moisture content were indicated by means of numerous curves. These curves are then used in predicting the optimum moisture content from liquid limit and plastic limit.

3. GENETIC ALGORITHM

A solution to solve the possible optimization problems based on natural selection is genetic algorithm. Finding solution in a GA is usually done after providing a population of binary or real strings, which are included in the form of decision variables. This genetic algorithm modifies the population of individual solutions repeatedly.

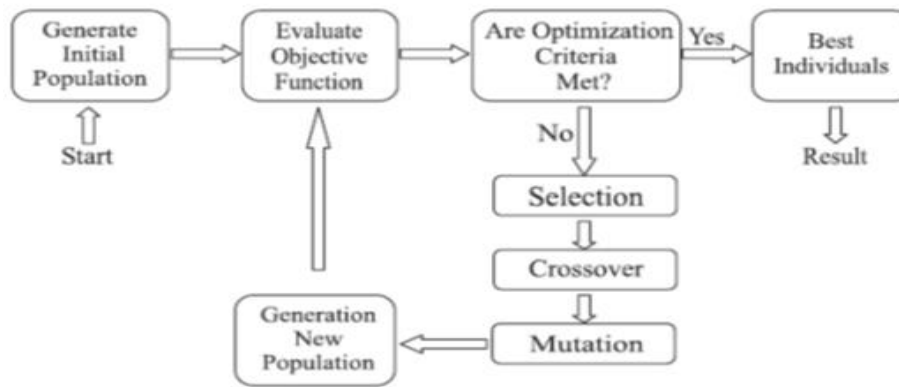


Figure 1: simple Genetic Algorithm Procedure

Each individual in the population representing a solution to the problem is called chromosome. Chromosome is usually a binary bit string. The chromosomes after going through successive iteration called generation. During each generation, the chromosomes are analyzed, using some fitness criteria. To create the next generation, new chromosomes are formed either by crossover operator or by a mutation operator. Using these operations, fitter members of the population are created with time. A new generation is formed by selecting, according to the fitness values and rejecting others in order to keep the population size constant. Fitter chromosomes have greater chance of being selected. After several generations, the algorithm concludes to the best chromosome, which represents the near optimum solution to the problem.

4. GENETIC OPERATIONS

Genetic variation is necessary for evolution. Genetic operators used in genetic algorithms are similar to those in the natural world. It mimics the process of Darwinian evolution to create populations from one generation to other. Various types of operators used in genetic algorithm are selection, crossover and mutation.

4.1 Selection

The primary objective of the selection operator is to select the best solutions and eliminate the bad solutions in a population, keeping the population size constant. It is based on the principle of select the best and discards the rest. It gives preference to better solutions by allowing them to pass on their genes to the next generation. It will also pass the best solutions from the current generation directly to the next generation without mutation; this is known as elitism. Selection process determines which solutions are to be preserved and allowed to reproduce and which ones to be died

4.2 Cross over

Crossover is a main genetic operator. It operates on two chromosomes at a time and will generate new chromosomes by combining both chromosomes features. It works by selecting any two solutions strings randomly from the mating pool and some portion of the strings is exchanged.

4.2 Mutation

Mutation operator is using for changing gene values. In this operator, a single bit is flipped to form a new offspring string. It prevents the genetic algorithm converging to a local minimum. This function is achieved by stopping the solutions becoming too close to one another and results in encouraged genetic diversity amongst solutions.

5. METHODOLOGY

The GA modeling is proposed to be done by using Scilab. A large data base is collected from laboratory measurements for analyzing the model. Scilab (matrix laboratory) is a fourth-generation programming language which is one of the two major open-source alternatives to MATLAB, the other one being GNU Octave. Even though the Scilab is similar to MATLAB, Scilab is preferred over it because of its easiness. Optimum moisture content depends on index properties of soil. To predict the optimum moisture content by using GA model six index properties of soil considered as the input for the model. Those input variables are a) liquid limit, b) plastic limit, c) percentage fines, d) percentage sand, e) percentage gravel, f) specific gravity.

5.1 Data collection

The database used for the GA modeling Consists of 200 soil investigation projects conducted in various geotechnical engineering laboratories in Ernakulum district, Kerala. The database for prediction of OMC mainly contains c- Φ soils. The selected input variable for prediction of OMC are Liquid Limit, Plastic Limit, %Fines, %Sands, % Gravel and Specific Gravity.

5.2 Data division

The whole collected data were divided into training, testing and validation sets. In total 82.5% of data were used for training and 17.5% used for testing and validation. The data is divided into two sets in such a manner that mean, standard deviation of two sets are equal or approximately equal. The data should be divided into two sets having mean and standard deviations are equal to minimize error.

Table1: division of data

PARAMETERS		TRAINING	TESTING
Liquid limit	Mean	50.44242	50.14286
	Standard deviation	10.55552	14.11413
Plastic limit	Mean	29.53939	34.14286
	Standard deviation	7.707691	10.8334
Percentage fines	Mean	36.51455	37.71357
	Standard deviation	16.66575	24.72923
Percentage sand	Mean	41.95576	39.35643
	Standard deviation	16.25371	20.7601
Percentage gravel	Mean	21.5903	22.93
	Standard deviation	16.61102	23.30403
Specific gravity	Mean	2.615697	2.669286
	Standard deviation	0.077823	0.094744
Optimum moisture content	Mean	18.73788	18.46429
	Standard deviation	2.55457	4.115937

5.2 Data division

The full algorithm was implemented by coding in Scilab5.5.1. A total of 165 data out of 200 data collected (82.5%) were used for training the model. An initial population of chromosomes was used for the development of the Genetic model. In this work an initial population of 1000 was selected and 500 generations were assigned. Each chromosome contains a variable array and an operator array. The variable array contained the coefficients and power terms of each input variables to the model. The coefficients of the variables were assigned a random number between 0 and 500 and the power terms were assigned a random number between -3 and +3. The operator array contained eleven slots, six of them for placing the input variables and the remaining five positions for placing the arithmetic operators connecting these variable terms. The input variables from training dataset were substituted in all the random equations generated by the model to obtain OMC. The OMC calculated from this equation was compared with the actual measured OMC to determine the error in prediction of values. The sum of squares of errors of all the data in training dataset and testing dataset was calculated for the generated equations of OMC.

6. RESULTS AND DISCUSSIONS

The genetic model was implemented by coding algorithm in Scilab 5.5.1. The division of whole data into training and testing sets was done using Microsoft Excel. Initial populations of 1000 random equations were generated by coding in Scilab. A mutation probability of 0.5 assigned. The entire process of selection, crossover and mutation was repeated for 1000 generations to find out the best solution. To obtain a best solution, the program was done for several generations by changing crossover and mutation probability. From the generated equations, finally the following equation found to be more accurate.

$$OMC = \left((486.2339 * WL^{0.4517}) + \left((221.8684 * WP^{0.4128}) \div (446.8984 * f^{-1.403}) \right) + (85.2602 * s^{-0.116}) + (84.697 * g^{-0.0534}) \right) \div (77.708 * G^{0.8508}) \dots (1)$$

Where,

WL = Liquid Limit (%)

WP = Plastic Limit (%)

f = Percentage fines (%)

s = percentage sand (%)

g = percentage gravel (%)

G = specific gravity

The correlation of predicted OMC with actual OMC was studied and It was found that it shows a good correlation.

Table 1: Correlation of data

	<i>Initial population</i>	<i>No. of generations</i>	<i>Correlation</i>
Training	1000	500	0.896682
Testing	1000	500	0.9460540

The performance of model was analyzed by plotting the calculated OMC from the obtained equation with actual OMC. Graphs were plotted for both training and testing data. Those graphs are shown in figure 2 and 3. From the graph plotted, we can see that the predicted OMC is approximately equal to the actual value. Thus the genetic algorithm model proves that it is a better alternate for prediction of OMC.

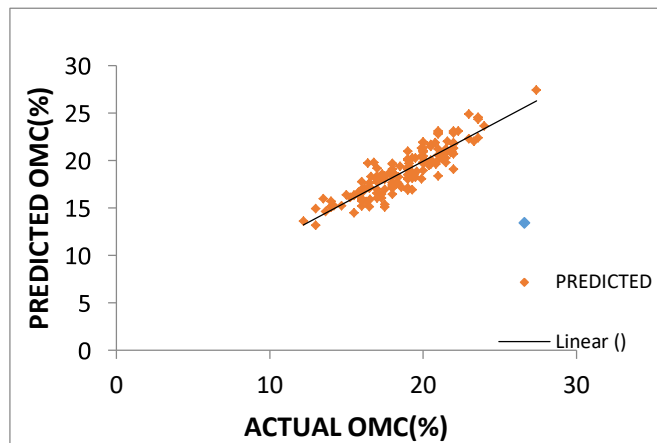


Figure 2: performance of the model with training dataset

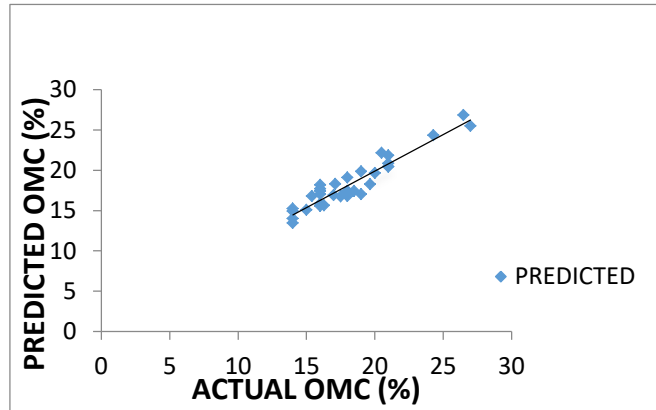


Figure 3: performance of the model with testing dataset

6.2 Sensitivity analysis

A study was conducted to know the effect of input parameters on the output parameter OMC. It was done by varying one input variable and keeping the other variables to their mean value. It shows how each input variable is related to OMC. Graphs are plotted to show the relation of each input variable with OMC.

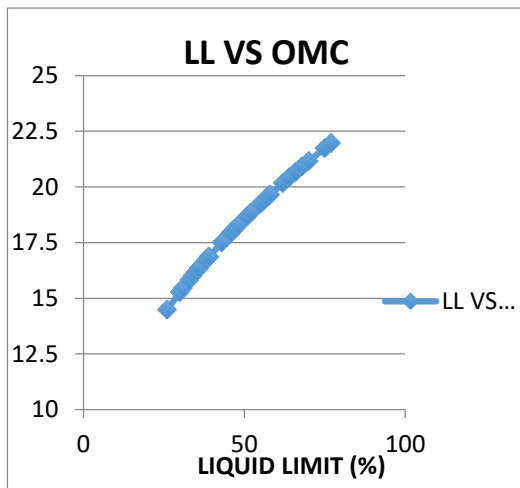


Figure 4: effect of liquid limit on OMC.

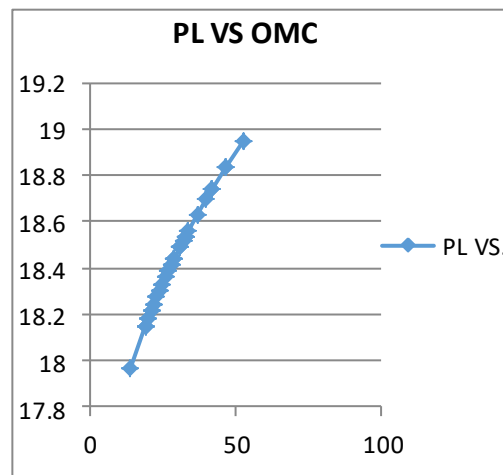


Figure 5: effect of plastic limit on OMC

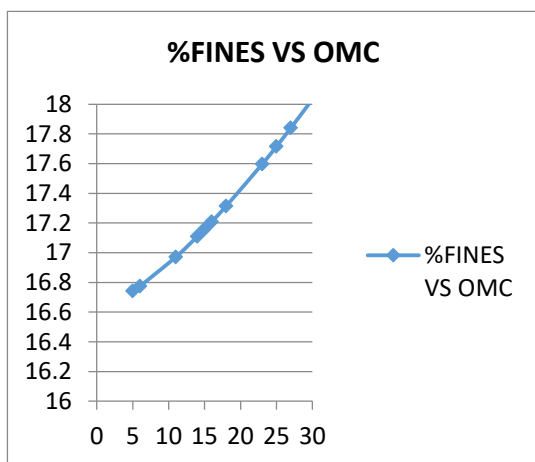


Figure 6: effect of percentage fines on OMC

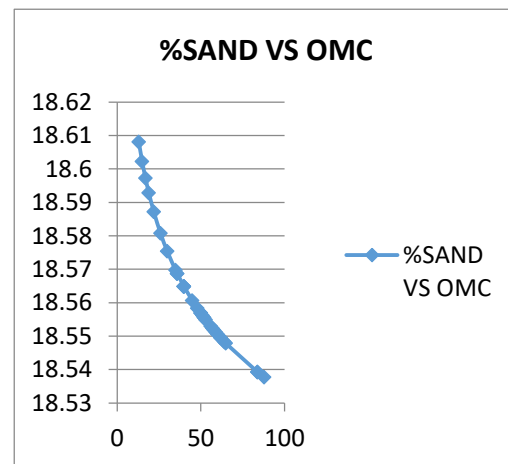


Figure 7: effect of percentage sand on OMC

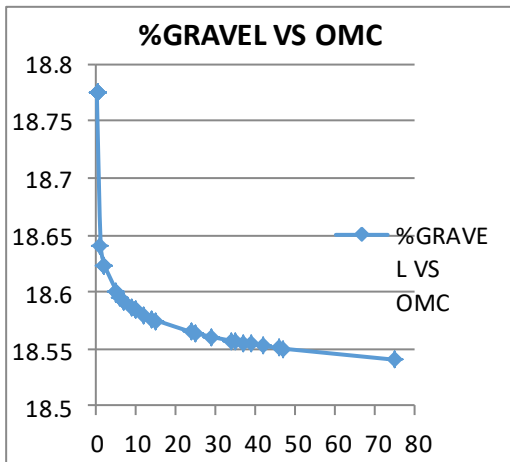


Figure 8: effect of percentage gravel on OMC

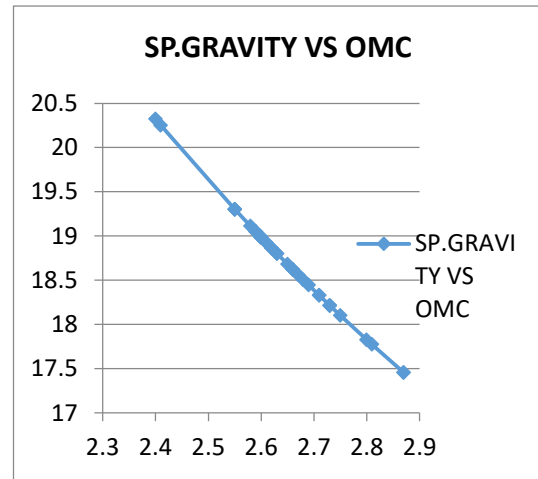


Figure 9: effect of specific gravity on OMC

From the graph obtained by drawing each input variables to study its influence on optimum moisture content, it is shown that OMC depend on all input parameters we choose. All six input parameters selected in this project shows great influence on OMC, some parameters shows a direct proportionality with OMC and some others shows an indirect proportionality with OMC.

7. ACKNOWLEDGEMENT

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8. CONCLUSION

The prediction of optimum moisture content of soils using laboratory techniques is laborious and difficult work. By using this software we can easily predict the OMC. The genetic algorithm model developed in this project proved that it is one of the easiest and better ways to predict OMC. The model was developed by using large database of 200 samples consisting of c- Φ soils. The prediction of OMC is done by using input variables as liquid limit, plastic limit, percentage fines, percentage sand, percentage gravel, and specific gravity. The developed model showed a good degree of accuracy. Hence it can be used as a best alternative to the prediction of OMC.

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