# Prediction of Optimum Moistiure Cntent using Genetic Algorithm

Fasna M..B.[1,*], Fathima Zuhara T. N.[2] and Sowmya V. Krishnankutty[3]

[1]Federal institute of science and technology, Mookkanooor
Kerala, India.

[2]Federal institute of science and technology, Mookkanooor
Kerala, India.

[3]Federal institute of science and technology, Mookkanooor
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-Φ 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-Φ 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.

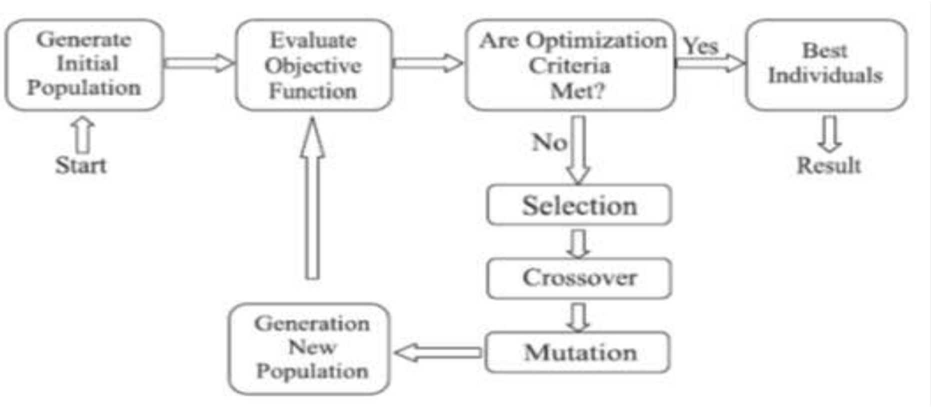


**Figure 1:** simple Genetic Algorithm Procedure

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 =

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

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

| | *Initial population* | *No. of generations* | *Correlation* |
|---|---|---|---|
| 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.

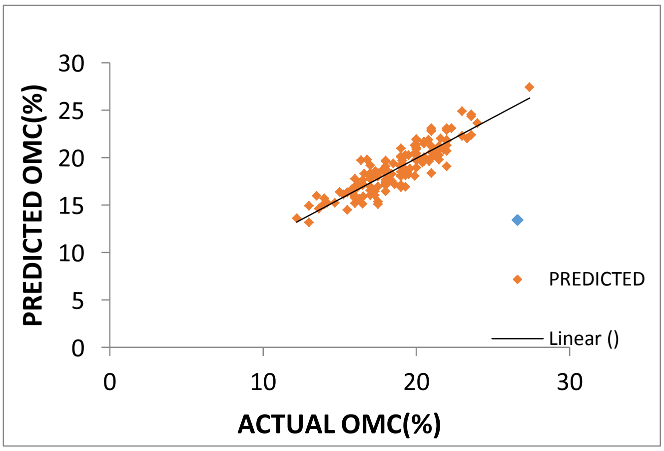


**Figure 2:** performance of the model with training dataset

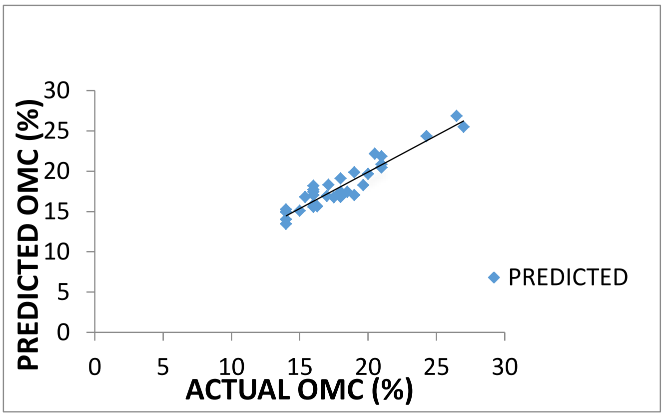


**Figure 3:** performance of the model with testing dataset

### *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.

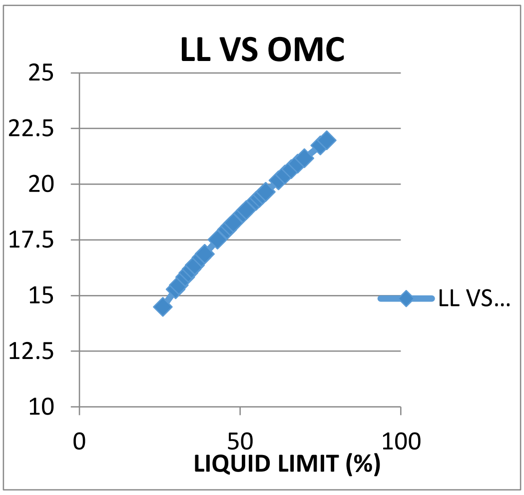


**Figure 4:** effect of liquid limit on OMC.

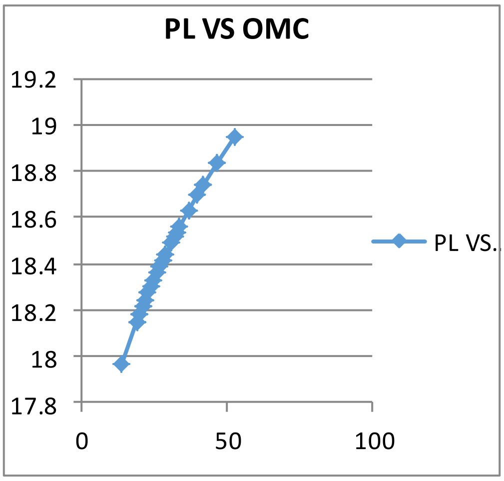


**Figure 5:** effect of plastic limit on OMC

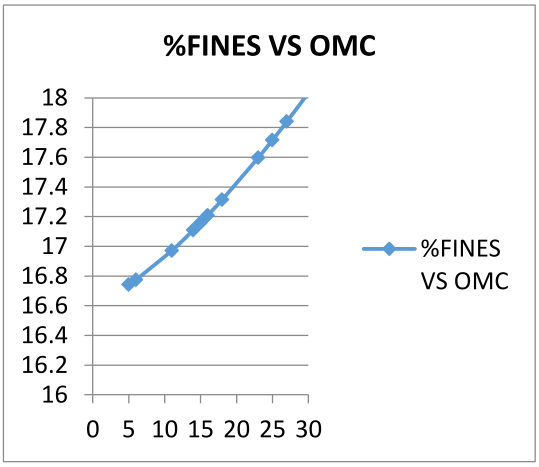


**Figure 6:** effect of percentage fines on OMC

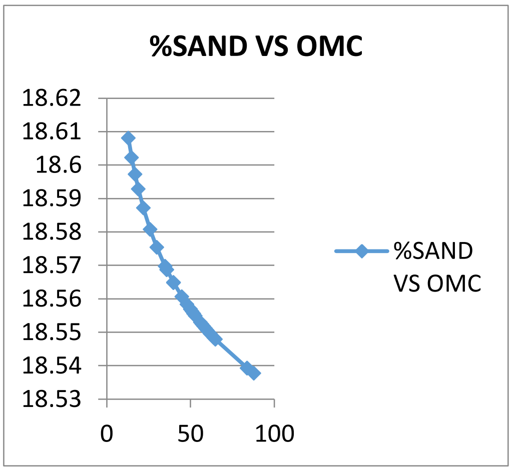


**Figure 7:** effect of percentage sand on OMC

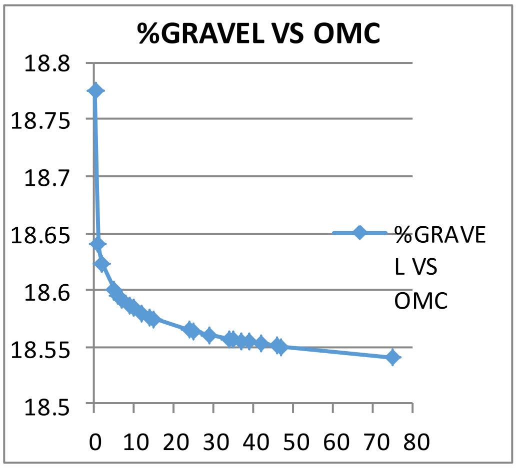


**Figure 8:** effect of percentage gravel on OMC

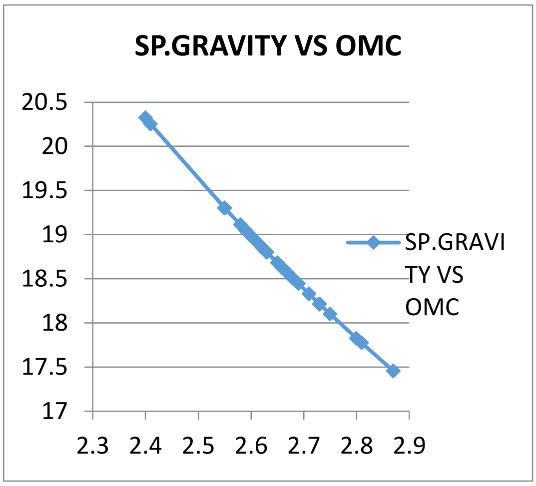


**Figure 9:** effect of specific gravity on OMC

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

The authors wish to thank Asst professor Sowmya V Krishnankutty for valuable and helpful discussions. We gratefully acknowledge technical and economic support from Civil engineering department, Federal Institute of Science And Technology, Kerala.

## 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.

## 9. REFERENCES

[1] C M Chan, L M Zhang, and Jenny T Ng, "Optimization of Pile Groups Using Hybrid Genetic Algorithms." Journal of Geotechnical and Geoenvironmental Engineering., vol. 135, no. 4, pp. 497–505, 2009.
[2] Al-Khafaji A.N, "Estimation of soil compaction Parameters by means of atterberg limit" Q. J. Eng. Geol. Hydrogeol., vol.26, no.4, pp. 359-368, 1993.
[3] Culshaw, M. G, "The provision of digital spatial data for engineering geologists", Bull Eng Geol Env, pp: 185–194, 2006.
[4] Blotz L, Bension, C. and Boutwell, G., "Estimating optimum water content and max.dry unit weight for compacted soils" J. Geotech Geoenvir Engg., vol.124, no. 9, pp. 907-912, 1998.
[5] Maziar Pasdarpour a, Mahmoud Ghazavi., "Optimal design of soil dynamic compaction using genetic algorithm and fuzzy system", journal of Soil Dynamics and Earthquake Engineering., vol. 29, pp. 1103-1112, 2009.
[6] A. Johari , A.A. Javadi , G. Habibagahi., "Modelling the mechanical behaviour of unsaturated soils using a genetic algorithm-based neural network", journal of Computers and Geotechnics., vol. 38, pp. 2-13, 2011.