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Application of Genetic Programming in the Field of Geotechnical Engineering - A Review

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Abstract. Geotechnical Engineering largely focused on the complex nature of soils and rocks. Because this complexity creates a high level of ambiguity in the imitation of these materials' nature. Genetic Programming (GP) has been initially developed by J. Koza (1992) and then used by many researchers in different areas including geotechnical engineering. This paper closely reviewed the application of GP in some areas of geotechnical engineering identified: settlement of the shallow foundation, bearing capacity of pile foundation, liquefaction assessment, estimation of pore water pressure, compaction parameters (OMC & MDD), soil-fiber composite assessment, free swell and swell pressure, the effectiveness of rolling dynamic compaction, prediction of soil water characteristic curve, and unconfined compressive strength (UCS). GP has been getting success over the years, because of its ability to find the relationship between the input variable and predict the output variable. This paper also discusses the future scope of GP in some unexplored areas of geotechnical engineering.

Keywords: modelling, genetic programming, geotechnical engineering.

1 Introduction

Geotechnical engineering deals with the study of geomaterials and their interaction with the environment. Soil is one of the complex engineering materials that behave non-linearly, exposed to environmental conditions. The heterogeneous and anisotropic nature of soil and rock is due to their origin and formation process (Shahin, 2015). This makes soil and rock difficult to predict in the atmosphere. In geotechnical engineering, the properties of soil and rock find out through various laboratory or field testing. But these laboratory and field testing are time-consuming and instruments are costly (Baghbani et al., 2021). Moreover, laboratory and field testing are limited to very few parameters required for particular testing experiments. On the contrary, numerical methods virtually analyze the complex nature of the material (Baghbani et al., 2021).

Currently, Artificial Intelligence (AI) is being used for finding various solutions to the problems that arise in the field of geotechnical engineering. AI can model complex and non-linear behavior of geotechnical material without considering the assumptions between the variables and the unknown. AI can create incomplete data by recognizing the patterns between the parameters (Shahin, 2015). There are various AI methods have been used in geotechnical engineering viz- Artificial Neural Network (ANN), Deep Learning (DL), Fuzzy inference system (FIS), Particle Swarm Optimization (PSO), Genetic Algorithm (GA), and Genetic Programming (GP) (Sterling and Lee, 1992; Gribb and Gribb, 1994; Gupta et al., 2004; Javadi et al., 2006; Armaghani et al., 2014; Bartlewska and Strzelecki, 2018).

This paper discusses the application of Genetic Programming (GP) in various areas of geotechnical engineering. GP is a simple pattern recognition method, that breeds the computer programs genetically to solve problems using reproduction, crossover, and mutation (Koza and Poli, 2005). GP works on the Darwinian principle of survival of the fittest computer program (Koza, 1992). This process is continued to get the final solution based on the termination criterion which can be either a correct solution to the problem (Koza, 1992) or an acceptable minimum error (Fatehnia and Amirinia, 2018).

2 Application of GP in Geotechnical Engineering

Geotechnical properties of soils such as liquefaction potential, compaction characteristics, free swell index, swell pressure, and unconfined compressive strength (Baziar et al., 2011; Alavi and Gandomi, 2011, 2012; Naderi et al., 2012; Soleimani et al., 2018; Bodour et al., 2022; Vishweshwaran et al., 2019) have been investigated by the application of GP techniques. Similarly, GP has been used to predict the behavior of geomaterials such as the prediction of soil water characteristic curve (Johari et al., 2006), settlement of shallow foundation (Razania and Javadi, 2007), bearing capacity of shallow foundation (Shahin, 2015), bearing capacity of pile foundation (Fatehnia and Amirinia, 2018), and in soil-fiber composite assessment (Kurugodu et al., 2018). From which a few identified areas are discussed in the subsequent section.

2.1 Prediction of soil parameters

Compaction Characteristics (OMC and MDD). Naderi et al. (2012) collected a database to estimate optimum moisture content (OMC) and maximum dry density (MDD) using GP which gives a highly precise model. The independent variables of the model are the soil classification properties, including % of fines (*FG*), % of sand (*S*), % of gravel (*G*), specific density (G_s), liquid limit (w_l) in % and plastic limits (w_p) in % and the dependent variables are OMC an MDD. The best model for OMC and MDD formulated based on GP is as follows:

$$\begin{aligned} OMC = {} & 4.573FG + 0.2602\left(G + w_L\right) - 0.2707w_P\left(FG + G_s\right) - 0.00533w_P^2(S+G) - 33.19 + \\ & 0.6683w_P^2 - 0.000119w_P^4 - 0.00417(FG - S)\left(S - w_p\right) - \frac{0.0984S}{G - FG + 0.174} + \frac{0.03731S}{S - FG + w_l} - \\ & \frac{0.1325S - 0.0889w_l}{G_s - S + w_p} + \frac{0.00245S}{G_s - G + 0.94} - \frac{0.0933w_p}{G - 2w_p} - \frac{16.88FG + 32.27}{w_p} - \frac{10.45FG}{G_s S} \end{aligned} \tag{1}$$

$$MDD = 0.8895w_p\left(w_p - G_{s/S}\right) - 0.5467S - 14.42G_s - 0.03122w_lG - 0.0364w_lw_p - 0.7021FG - 0.0101w_l^2 - 0.0004035G\left(S - w_l^2\right) - \frac{23.39w_l + 0.0364S}{w_p} + \frac{7.205w_l}{G_s} - \frac{0.09076Sw_p}{FG} + 161 + \frac{0.5467G + 0.6113FG - 0.0011G^2FG - 0.3027}{S} - \frac{7.842w_p}{G_s - 0.9623} + \frac{0.00464w_p}{G - 0.9623} + \frac{0.04G}{FG - S/G} \tag{2}$$

The comparison of GP-based models (Eq.1 and Eq. 2) performed better than simple regression analysis (Gunaydin 2009), ANN model (Gunaydin 2009), and MLR-based model in terms of coefficient of correlation and lowest regression errors.

Unconfined compressive strength (UCS). Several researchers developed a few models for estimation of UCS using traditional regression techniques, the ANN model (Mozumdar and Laskar 2015), and MGGP based model. The MGGP model for the prediction of UCS of geopolymer stabilized clayey soils is as follows:

$$UCS = PI\left(0.161 - 0.0723\sqrt{S}\right) + 0.221\left(FA + \sqrt{FA}\right) - 0.0118\frac{Na}{Al} + 0.212\left(S^{\frac{A}{B}} - 0.0577S^{\frac{Na}{Al}}\right) + 1.31S \times \left[1 - \frac{0.222}{\frac{Na}{Al}} - 0.009S + 0.00206\sqrt{\frac{S}{\frac{Na}{Al}}\left(FA - \sqrt{FA} + \sqrt{7.92PI}\right)}\right] - 5.63 \tag{3}$$

*w*here, *PI* is the plasticity index, *S* is the percentage of ground granulated blast furnace slag, *FA* is the percentage of fly ash, and *A/B* is the alkali to binder ratio. The proposed MGGP model (Eq. 3) for predicting the UCS of geopolymer stabilized clayey soils gives better performance as compared with the other methods and models (Soleimani et al. 2018). Similarly, another GP-based model was also proposed by Kurugodu et al. (2018) for predicting the UCS of soil-fiber composite in terms of strength improvement factor.

Free swell index and swell pressure. A free swell of soil is the ratio of the difference in final volume to the initial volume, expressed in percentage. Swell pressure is defined as the load required to bring the specimen back to its initial condition (void ratio). If the soil free swell value is more than 50% then it causes considerable damage to the lightweight structures through the cyclic swell shrink phenomenon (Nelson and Miller, 1992). Vishweshwaran et al. (2019) proposed a GP-based model to account for the percentage of free swell (FS) and swelling pressure (SP) and it is as follows:

$$FS(\%) = 6.02 + 0.037(\%\,clay) + 0.038 \times w_L \times A - 0.49 \times w_0 \times A \tag{4}$$

$$SP = 4.35 + 0.02 \times w_0 \times w_P^2 + 0.00025 \times w_L \times (\%\,clay)^2 - 3.54 \times w_P - 1.7 \times D \times w_P - 24.61 \times w_0 \times A \tag{5}$$

where w_L is the liquid limit, w_P is the plastic limit, w_0 is initial water content, *A* is the activity of clay, and *D* is depth. The predicted values of *FS* and *SP* were found close to the measured values and the above equations (Eq.4 and Eq.5) are applicable for clay shales of the Tabuk region.

Soil Liquefaction. Several researchers tried to model liquefaction potential using finite elements, analytical methods, empirical methods, and neural network-based models (Javadi et al., 2006). But these methods cannot provide an accurate and reliable prediction of lateral displacement for cases with measured lateral spreading less than about 1 m (Seed et al., 2003) except ANN. ANN can be trained to learn the relationship between the input (soil) and output (liquefaction-induced lateral displacement) variables. However, the main disadvantage of the ANN model is its black-box nature. Therefore, a new technique of genetic programming is introduced for the prediction of liquefaction. A database of 485 SPT-based case histories, collected by Youd and Bartlett (2002), is used for training and validation of GP models developed for two specific site conditions.

Case 1: for free space

$$Dh_c = -163.1\frac{1}{M^2} + 57\frac{1}{R\times F_{15}} - 0.0035\frac{T_{15}^2}{W\times D50_{15}^2} + 0.02\frac{T_{15}^2}{F_{15}\times D50_{15}^2} - 0.26\frac{T_{15}^2}{F_{15}^2} + 0.006T_{15}^2 - 0.0013W^2 + 0.0002M^2\times W\times T_{15} + 3.7 \tag{6}$$

Case 2: Gently sloping ground condition

$$Dh_c = -0.8\frac{F_{15}}{M^2} + 0.0014F_{15}^2 + 0.16T_{15} + 0.112S + 0.014\frac{S\times T_{15}}{D50_{15}} - 0.D50_{15} + 1.14 \tag{7}$$

where Dh_c is the horizontal displacement, M is the earthquake magnitude, R nearest horizontal distance of the seismic energy source to the site, T_{15} is the cumulative thickness of saturated cohesionless soil layers with corrected SPT number less than 15, F_{15} average fines content (< 75µm) for granular materials within T_{15}, $D50_{15}$ is the average mean grain size for granular materials within T_{15}, W free face ratio, and S slope of the ground surface. A comparison of the results shows that the result predicted by the proposed GP models provides a good set of results and improvement in the results over the commonly used MLR model (Javadi et al., 2006).

Alavi and Gandomi (2011) developed GP-based models (Eq.8, Eq.9, and Eq.10) using linear genetic programming (LGP), gene expression programming (GEP), multi-expression programming, and Gandomi and Alavi (2012) developed GP based models (Eq.11) using multigene genetic programming (MGGP) for deciding the liquefaction (LC) and non-liquefaction soil conditions are as follows:

$$LC_{LGP} = \frac{1}{\sigma_v'^2}\left(a_{max}\sigma_v'^2 - 4q_c\sigma_v' - 9R_f\sigma_v' + 54\sigma_v' + 9\sigma_v - 54M_w - 378\right) \tag{8}$$

$$LC_{GEP} = a_{max} - \frac{1}{\sigma_v'}\left(\frac{R_f}{a_{max}} - 5a_{max}\right) + \frac{q_c - -\left(M_w - q_c\right)R_f}{2q_c - \sigma_v - 3} + \frac{4 - R_f}{q_c + 2} \tag{9}$$

$$LC_{MEP} = a_{max} + \frac{1}{\sigma_v^{'}}\left(4a_{max} + 4M_w - 4q_c + \frac{9}{4\sigma_v^{'}} - \frac{9R_f}{4} + \frac{\sigma_v^{'}}{4} - 4R_f\frac{2\left(q_c - a_{max} - M_w\right)^2 + M_w}{\sigma_v^{'}}\right) \quad (10)$$

$$\begin{aligned} LC_{MGGP} = {} & 0.5491 + 0.9634 \times 10^{-15} R_f q_c^4 \ln\left(q_c\right) - 0.6553 q_c + 0.6553 \ln\left[\tan\left(a_{max}\right)\right] + \\ & 0.1288 R_f + 0.2576 M_w + 0.1288 \ln\left(\sigma_v^{'}\right) q_c + 0.2058 \ln\left[\left|\ln\left(a_{max}\right)\right|\right] + \\ & 0.2058 \ln\left(a_{max}\right) R_f - 0.2861 \times 10^{-6} \sigma_v \sigma_v^{'}\left(\sigma_v + q_c\right) - 0.2861 \times 10^{-6} q_c^2 \sigma_v^{'2} \end{aligned} \quad (11)$$

where σ'_v is effective stress, R_f is sleeve friction ratio, a_{max} is maximum horizontal ground surface acceleration, q_c is the cone tip resistance, M_w is earthquake moment magnitude, and σ_v is total stress at the same depth. If the output of equations (8) to (11) is greater than or equal to 0.5, the condition is marked as "liquefied", otherwise, it is marked as "non-liquefied". The accuracy of the GP models in terms of training and validation as follows:

Table 1. Performance of GP models in terms of training and validation

GP model	Training (%)	Validation (%)
LGP	90	94.64
GEP	88.82	92.86
MEP	86.47	85.71
MGGP	90	96.4

Another successful application of GP in the assessment of soil liquefaction potential was carried out by Rezania et al. (2010), and Gandomi and Alavi (2013) developed a GP model coupled with orthogonal least squares for predicting the soil capacity energy required to trigger soil liquefaction.

2.2 Prediction of soil behavior

Settlement of shallow foundation. Rezania and Javedi (2007) used 173 standard penetration test (SPT) test results collected from seven different studies, compiled by Shahin et al. (2002) used for the development and verification of the GP model. The results of the proposed GP model are compared with other traditional and Artificial Neural Network (ANN) models. Eq. (12), (13), and (14) are the GP model developed for the settlement of shallow foundations by Razania and Javadi (2007), Shahnazari et al. (2014), and Shahin (2015), respectively.

$$S_c = \frac{q(1.802B + 4.62) - 346.15D_f}{} + \frac{11.22L - 11.11}{} \tag{12}$$

$$S_c = \frac{2.5B\left(\frac{N}{B} - 1 + N^2\frac{B+1}{D_f + 0.16B} + \frac{2B - N}{L}\,{}^{L} + \frac{q}{N}\right)}{\left(N + \frac{D_f}{B}\left(B - \frac{L}{B}\right) + \frac{B}{N}\right)} \tag{13}$$

$$S_c = -8.327\frac{q}{N^2L} + 8.849\frac{q}{N^2} + 2.993\frac{B\sqrt{q}}{N} - 0.651\frac{B\sqrt{qD_f}}{N} + 2.88 \tag{14}$$

where, S_C is the predicted settlement in mm, q is the net applied footing pressure in kPa, B is the footing width in m, D_f is the footing embedment depth in m, N is the average SPT blow count and L is the footing length in m. Comparing the results obtained from the GP models (Eq.12, Eq.13, and Eq.14) and traditional models along with the ANN model indicates that the GP models outperform the other models. The results obtained from the proposed GP model (Eq.14) and measured settlement were compared with the results predicted through the ANN model developed by Shahin et al. (2002) and other three traditional methods based on cone penetration test (CPT) and standard penetration test (SPT) given by Meyerhof (1965), elastic-isotropic half-space equation given by Schultze and Sherif (1973) and CPT and dilatometer test (DMT) given by Schmertmann (1978) as shown in figure 1. It can be observed that Shahin (2015) developed an evolutionary polynomial regression (EPR) based model and ANN model that outperformed the other traditional methods for the prediction of settlement of shallow foundations on cohesionless soil in terms of performance measures including coefficient of correlation (r), coefficient of determination (R^2), root mean squared error (RMSE), mean absolute error (MAE) and the ratio of average measured to predicted outputs (μ).

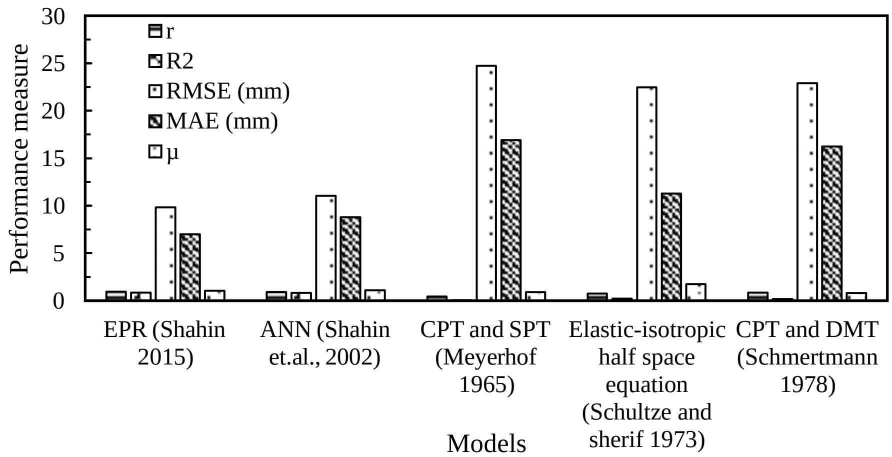

Fig. 1. Performance of measures of various models.

Bearing Capacity of Pile foundation. Shahin (2015) prepared a model based on EPR for driven piles and drilled shafts consisting of 79 in situ driven pile load tests and 94 in-situ drilled shaft load tests as well as cone penetration test results. The data were collected from different locations, with different soil conditions including cohesive and cohesionless soil. The drive pile load tests include tension and compression loading conducted on concrete and steel piles with different shapes and ranges in diameter between 250 mm to 900 mm and embedment lengths between 5.5 m to 41.8 m. The drilled shaft load tests were conducted on straight and belled concrete piles that have stem diameters ranging from 305 to 1798 mm and embedment lengths from 4.5 m to 27.4 m. The models for yield capacity (Q_u) of driven steel pile (Eq. 15), driven concrete pile (Eq. 16), and drilled shafts (Eq. 17) are as follows:

$$Q_u = -2.227\frac{D\bar{q}_{c_{tip}}}{\sqrt{\bar{q}_{c_{shaft}}\bar{f}_{s_{shaft}}}} + 0.096DL + 1.714\times 10^{-4}D^2\bar{q}_{c_{tip}}L - 6.279\times 10^{-9}D^2L^2\sqrt{\bar{q}_{c_{tip}}\bar{f}_{s_{tip}}} + 243.39 \tag{15}$$

$$Q_u = -2.277\frac{D\bar{q}_{c_{tip}}}{\sqrt{\bar{q}_{c_{shaft}}\bar{f}_{s_{shaft}}}} + 0.096DL + 1.714\times 10^{-4}D^2\bar{q}_{c_{tip}}\sqrt{L} - 6.279\times 10^{-9}D^2L^2\sqrt{\bar{q}_{c_{tip}}\bar{f}_{s_{tip}}} + 487.78 \tag{16}$$

$$Q_u = 0.68778L^2\sqrt{\bar{f}_{s_{shaft}}} + 1.581\times 10^{-4}B^2\sqrt{\bar{f}_{s_{shaft}}} + 1.294\times 10^{-4}L^2\bar{q}^2_{c_{tip}}\sqrt{D} + 7.8\times 10^{-5}D\bar{q}_{c_{shaft}}\bar{f}_{s_{shaft}}\sqrt{\bar{f}_{s_{tip}}} \tag{17}$$

where, D is the pile perimeter for driven piles or piles stem diameter for drilled shafts in mm, B is the drilled shaft base diameter in mm, L is the pile embedment length in m, and $\bar{q}_{c_{tip}}$ is the weighted average cone point resistance over pile tip failure zone in MPa, $\bar{f}_{s_{tip}}$ is the weighted average cone sleeve friction over pile tip failure zone in kPa, $\bar{q}_{c_{shaft}}$ is the weighted average cone point resistance over pile embedment length in MPa, and $\bar{f}_{s_{shaft}}$ is the weighted average cone sleeve friction over pile embedment length in kPa. The performance of EPR-based models is compared with the other four models for driven piles as shown in Figure 2. For driven piles, the methods considered for comparison include the ANN model developed by Shahin (2010), the European method developed by De Ruiter and Beringen (1979), the LCPC method developed by Bustamante and Gianeselli (1982) and Alsamman (1995) method. From figure 2, it is clear that the performance of the EPR model is good and outperforms the other methods except for Alsamman's (1995) model.

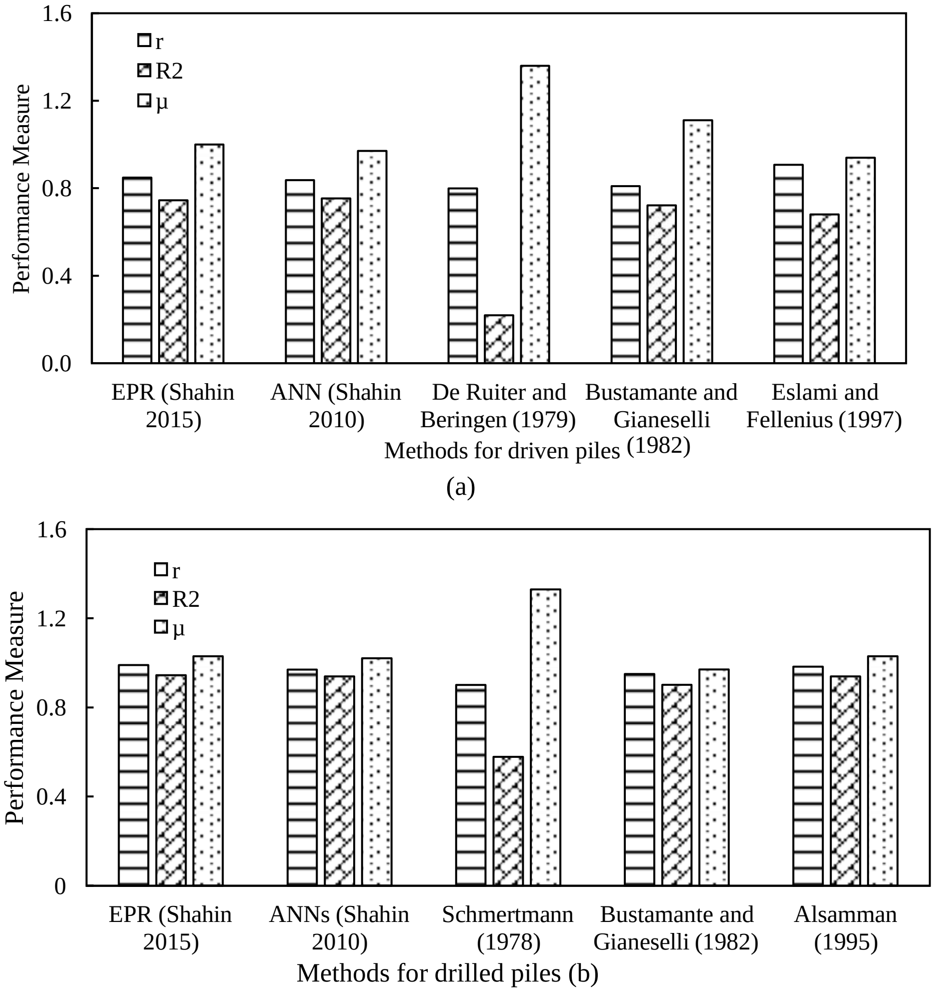

Fig. 2. Performance measure – (a) Methods for driven piles (b) methods for drilled piles

Soil water characteristic curve (SWCC) SWCC is one of the most important concepts for any model in the case of unsaturated soil behavior because it describes the variation of soil suction with changes in water content (Fredlund et al. 2002). In unsaturated soil behavior shear strength, volume change, diffusivity, and adsorption properties affect the SWCC (Fredlund and Rahardjo 1993). SWCC can find out in the laboratory using a pressure plate, Buchner funnel, tensiometers, pressure membranes, and filter paper, heat dissipation sensor. But these experiments are costly and time-consuming. Therefore, researchers proposed several empirical methods to estimate the SWCC for soils. Johari et al. (2006) have proposed a GP model for the prediction of SWCC of soils using some independent parameters like initial void ratio, initial gravimetric water content, the logarithm of suction normalized for atmospheric air pressure, clay content, and silt content and the dependent parameter consist of the gravimetric water content corresponding to the assigned input suction. Researchers compiled 186 database results from pressure plate tests with the grain size distribution of the reported soil type and used that database for the development and validation of the model. The model generated based on GP is as follows:

$$Y = 0.794\left(X_2 + 0.215\right)\left\{\left\|\left[(0.116^{X_3} \times X_4^{X_5})^{\left(X_1 + 0.234\right)} + \left(X_4^{0.368\left(\frac{X_5}{X_4}\right)}\right) \times \left(X_3^{X_1} - X_3\right)\right]X_4\right\}^{X_3^2} \quad (18)$$

$$w = X_2\left(\frac{Y}{Y_0}\right) \quad (19)$$

where Y is predicted water content, Y_0 is predicted initial water content (at suction 0.2kPa), X_1 is an initial void ratio, X_2 is initial water content, X_3 is log (suction in KPa)/p_a, p_a is atmospheric pressure (taken as 100 kPa), X_4 is clay content (%), X_5 is silt content in % and w is adjusted water content. The proposed GP model compared with the conventional methods indicated its superior performance for the prediction of SWCC.

Estimation of pore water pressure. Soil water characteristic curve and permeability function are the two input components required for the computation of pore water characteristic curve (PWCC) using the unsaturated seepage modelling for estimating pore water pressure. MGGP was used for generating pore water pressure profile (PWPP) in unsaturated soil (Garg et al. 2014). The main advantage of MGGP is that it can predict the PWPP directly without the need to perform numerical solutions to highly non-linear Richard's equation. The best fit MGGP model is as follows

$$MGGP = 1357.0099 + 0(-737.0697) \times \left[\sin\left(\tan^{-1}\left(\tan^{-1}x_5\right)^2\right)\right] - 973.9708 \times \tan^{-1}\left(e^{\tan^{-1}\left(x_5\right)}\right) + 2.8049e^{\tan^{-1}\left(x_3\right)} + e^{\tan^{-1}x_5^{\,2}} + e^{\tan^{-1}x_3} +$$

$$\left(x_2 + x_5\right) - 598.4632 \times \left(p^{p^{\left(x_2, \tan^{-1}x_5\right), x_5}}\right) + (0.0001063) \times \left(p^{\left(x_5, \cos\left(x_5\right), +\left(x_5\right)\right)}\right) + 48.5523 \times \sin\left(e^{\tan^{-1}\left(x_5\right)^2}\right) \quad (20)$$

where x_1 is the air entry value, x_2 is residual volumetric water content, x_3 is saturated volumetric water content, x_4 is the slope, and x_5 is depth. The above MGGP model (Eq. 20) gives the explicit mathematical relationship between input and output components which can also be used offline to estimate the pore water pressure.

3 Conclusion

Earlier traditional methods (i.e., SPT, CPT, DMT, etc) were used in geotechnical engineering for the estimation of soil properties but due to time economy constraints, people started using empirical, numerical, and finite element methods. But the accuracy of these methods limits their usage in the above-mentioned areas of geotechnical engineering. Thereafter, different Artificial Intelligent (AI) methods including ANN, GA, GP, PSO, and DL used in geotechnical engineering. In this review paper, applications of Genetic Programming (GP) in geotechnical engineering have been discussed with the help of previous studies. GP models provide more accurate solutions than other traditional and ANN methods in terms of r, R^2, RMSE, MAE, and µ. The accuracy of GP models depends on the selection of input parameters which decide the accuracy of the output parameter. The paper discusses a detailed review of settlement of the shallow foundation, bearing capacity of pile foundation, soil liquefaction, soil water characteristics curve, compaction parameters, pore water pressure, unconfined compressive strength, free swell and swell pressure. Different input parameters were identified in the above-mentioned areas and successfully used in the model for the prediction of the solution. Overall, GP has been successfully used and solved the various problems associated with the different areas in geotechnical engineering as compared with other models and methods discussed in this paper.

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