Primljen / Received: 19.9.2021.
Ispravljen / Corrected: 13.4.2022.
Prihvaćen / Accepted: 30.6.2022.
Dostupno online / Available online: 10.10.2022.

Statistical investigation on plastic waste recycling by reusing in soil

Authors:

Masoomeh Khodabakhshi, MCE
University of Guilan, Iran
Faculty of Engineering
Department of Civil Engineering
m.khodabakhshi.s@gmail.com

Prof. **Mahyar Arabani**, PhD. CE
University of Guilan, Iran
Faculty of Engineering
Department of Civil Engineering
arabani@guilan.ac.ir
Corresponding author

Research Paper

Masoomeh Khodabakhshi, Mahyar Arabani

Statistical investigation on plastic waste recycling by reusing in soil

Recycling and reusing plastic waste are key options for ameliorating its negative effects on the environment and the economy. This paper proposes evolutionary polynomial regression (EPR) as a powerful technique to predict the compressibility behavior of sand and high-density polyethylene (HDPE) mixtures. In the investigation, a series of large-scale oedometer experiments were conducted. The results of the coefficients of lateral earth pressure and volume compressibility coefficients of different mixtures were used to develop EPR models. The model parameters were evaluated by sensitivity analyses. The results showed that the best developed EPR model is robust for estimating the characteristics of sand and HDPE mixtures.

Key words:
plastic waste, high-density polyethylene, large-scale oedometer test, EPR, environmental geotechnics

Prethodno priopćenje

Masoomeh Khodabakhshi, Mahyar Arabani

Statističko istraživanje recikliranja plastičnog otpada ponovnom uporabom u tlu

Recikliranje i ponovna uporaba plastičnog otpada ključna je za ublažavanje njegovog negativnog utjecaja na okoliš i gospodarstvo. Ovaj rad predlaže evolucijsku polinomnu regresiju (eng. *Evolutionary Polynomial Regression* - EPR)) kao snažnu metodu za predviđanje stišljivosti pijeska pomiješanog s polietilenom visoke gustoće (HDPE). U svrhu istraživanja proveden je niz opsežnih pokusa pomoću velikog edometra. Za izradu EPR modela korišteni su rezultati koeficijenta bočnog pritiska tla i modula promjene volumena mješavina. Kako bi se ocijenili parametri modela, provedene su analize osjetljivosti. Rezultati su pokazali da je EPR model učinkovit za procjenu karakteristika mješavine.

Ključne riječi:
plastični otpad, polietilen visoke gustoće, veliki edometar, EPR, geotehnika i zaštita okoliša

1. Introduction

Global warming is caused by greenhouse gases, such as methane, emitted from use of fossil fuels. Ackerman (2000) [1] showed that most or all organic waste in landfills decays anaerobically and most carbon is gradually released to the atmosphere, of which approximately half is as carbon dioxide and the remainder as methane. Release of the latter is problematic because for the same amount of carbon release, methane has a 21 times greater global warming potential than carbon dioxide. When waste is the form of litter or small, uncontrolled, uncompacted dump sites, it poses potentially severe risks to sanitation, public health, and aesthetics. However, the decay of waste under these conditions is aerobic, releasing virtually all carbon as carbon dioxide, instead of as methane. Plastic waste created daily emits considerable carbon dioxide, which is a greenhouse gas. A study of the U.S. Environmental Protection Agency found that at least 114 million ton of carbon dioxide-equivalent gas is annually emitted from 130 plastic-manufacturing facilities and related power plants equivalent to 57 "average-sized" coal-fired power plants [2]. Therefore, the recycling/recovery/management of plastics, which form a significant fraction of municipal solid waste, is a principal method for mitigating environmental problems and allowing reuse of raw materials. Depending on the initial usage, the types of plastic waste are polyethylene terephthalate (PET), high-density polyethylene (HDPE), low-density polyethylene (LDPE), polypropylene (PP), and polystyrene (PS). Figure 1 shows a bar graph of demand-based classification of plastics by type [3]. The horizontal axis represents the demand breakup of plastics in percentage, and the vertical axis the type of plastics. Other types of plastics such as PET are included in the bar labeled "others." This bar graph shows that PP, polyvinyl chloride (PVC), and HDPE have the largest shares of plastic consumption.

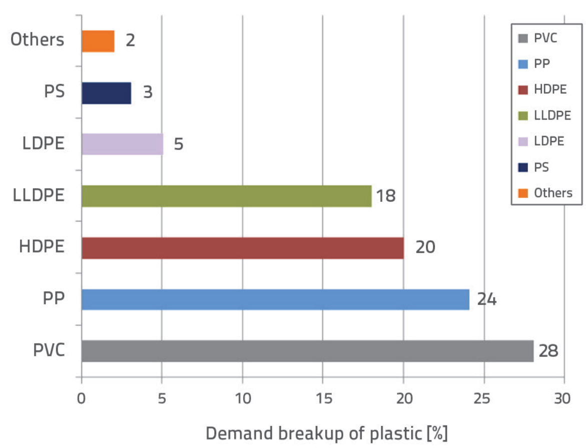

Figure 1. Demand-based classification of plastics by type [3]

Various studies have investigated the use of plastics to improve soil, some of which are discussed below.

Choudhary et al. [4] incorporated HDPE strips as reinforcements in local sand and conducted a series of laboratory California bearing ratio (CBR) tests on unreinforced and randomly oriented HDPE strip-reinforced sand specimens. The elasticity and the resistance to deformation were reported to considerably increase. They suggested the use of waste plastic strip-reinforced soil to reduce the stabilization cost of subgrade soils and promote the safe disposal of these waste materials in an environmentally friendly manner.

Kalumba [5] utilized waste from HDPE shopping bags to reinforce two selected sandy soils (Klipheuwel and Cape flat sands). They investigated strips of shredded plastic materials with different diameters and aspect ratios as reinforcements for sandy soils. Laboratory results demonstrated that the addition of HDPE strips affects the shear strength parameters of a mixture.

Kumar et al. [6] studied the reinforcing effects of plastic waste strips on soil by conducting a series of standard proctor and unsoaked CBR tests. Low-plasticity silt as per the Indian Standard Soil Classification System and LDPE were employed. They concluded that soil with 6 % plastic waste can be effectively used for soil stabilization in an environmentally friendly and economical manner.

Rakic et al. [7] classified municipal wastes according to their dominant effect and properties and using various existing classification schemes. Based on the cumulative particle size distribution curves of different municipal wastes from the Ada Huja landfill, plastic waste was determined to have the highest weight percentage in the landfill.

Abukhettala et al. [8] investigated geotechnical properties of plastic waste material usage in subgrade soils. The results showed this strategy can improve the strength, reduce the thickness, and decrease road or pavement structure costs. They suggested that partial replacement may prove useful for road subgrade applications.

Hassan et al. [9] examined engineering properties of a soil mixed with two fiber-shaped waste materials (polyethylene and PP). Soil stabilization with these fibers efficiently improved the strength properties of the soil materials for engineering projects. The length and content of the fibers affected the strength properties of the stabilized soils.

Until now, research on the behavior of mixtures of HDPE chips and sand has been insufficient, particularly using large oedometers. The objective of this study was to estimate the deformation characteristics of sand mixtures with and without HDPE chips by developing an evolutionary polynomial regression (EPR) model that helps soil improvement and reduces environmental pollution.

2. EPR model construction

Generally, there are two well-known types of data-driven modelling and computational intelligence: genetic programming (GP) and artificial neural networks (ANNs). ANNs are alternatives proposed as modelling tools inspired by the structure of the human brain. They learn from experience and generalize by detecting patterns and relationships in data.

GP is an evolutionary algorithm approach that uses a population of unfit programs, a fitness function, and multiple evolved generations. Despite its merits, GP tends to produce functions that grow in length over time and is not very powerful in finding a constant. Giustolisi and Savic [10, 11] introduced EPR, which is used in hydroinformatics and environmental problems. It is an evolutionary computing-based, data-driven method that operates on a huge volume of data to elucidate complex and nonlinear relationships between system variables. EPR is a two-stage technique; in the first stage (structure identification), a genetic algorithm (GA) searches for structures, and in the second stage (parameter estimation), constant values are estimated by solving a least-squares (LS) linear problem. A rule-based program comprising 56 unique rules transforms these models algebraically via a GP evolutionary process as expressed in the right-hand side of the following equation:

$$y = \sum_{j=1}^{m} a_j\, z_j + a_0 \tag{1}$$

where y denotes the LS estimate of the target value, a_j represents an adjustable parameter for the j^{th} term, a_0 is an optional bias, m is the number of terms or parameters in the expression, z_j is a transformed variable that is a function of the independent variables, inputs $(x_1,x_2,\ldots,x_k)$ are evaluated at the j^{th} data point, and k is the number of input variables.

To develop an EPR-based model, Eq. (1) should first be transformed into Eq. (2).

$$y_{N\times1}(\theta,Z) = [I_{N\times1} \quad Z^{j}_{N\times M}] \times [a_0 \quad a_1 \quad \ldots \quad a_m]^T = Z_{N\times d} \times \theta^T_{d\times1} \tag{2}$$

Where $y_{Nx1}(\theta,Z)$ represents the LS estimate vector of N target values, θ_{1xd} is the vector of d=m+1 parameters for a_j, j=1:m, Z_{Nxd} denotes a matrix formed by I for bias a_0, and m is a vector of variables z_j, which for a fixed "j" is a product of the independent predictor vectors of the variables or the inputs , i.e., $X = \langle X_1X_2\ldots X_k\rangle$.

In this method, a global search algorithm is implemented to obtain the compositions of the input variables and the exponents of the inputs simultaneously based on a user-defined cost function. The matrix of inputs X is expressed as

$$x = \begin{bmatrix} x_{11} & \cdots & x_{1k} \\ \vdots & \ddots & \vdots \\ x_{N1} & \cdots & x_{Nk} \end{bmatrix} = \begin{bmatrix} X_1 & X_2 & \cdots & \cdots & X_k \end{bmatrix} \tag{3}$$

where the k^{th} column of X contains the candidate variables for the j^{th} term of Eq. (2). Thus, one can write the j^{th} term of Eq. (2) as follows:

$$Z^{j}{}_{N\times1} = [(X_1)^{ES(J,1)}.(X_{21})^{ES(J,2)}\ldots\ldots\ldots\ldots(X_k)^{ES(J,k)}] \rightarrow j = 1\ldots..d \tag{4}$$

where: z^j is the j^{th} column vector whose elements are products of the candidate inputs and ES denotes the matrix of the exponents. The problem is to find the matrix, ES_{mxk}, of the exponents whose elements take values within user-defined bounds. For instance, if the candidate exponents for the columns in X are selected as EX = [0, 1, 2], the number of terms (m) is taken as 4, and the number of candidate variables (k) is 3. Consequently, the polynomial regression problem is to find the matrix of exponents, ES_{4x3}. An example of this matrix is as follows:

$$ES_{4\times3} = \begin{bmatrix} 1 & 0 & 0 \\ 1 & 1 & 0 \\ -1 & 0 & 1 \\ 0 & 1 & -1 \end{bmatrix} \tag{5}$$

Using this matrix in Eq. (4), the following set of mathematical expression is obtained:

$$\begin{aligned} Z_1 &= (X_1)^1 \cdot (X_2)^0 \cdot (X_3)^0 = X_1 \\ Z_2 &= (X_1)^1 \cdot (X_2)^1 \cdot (X_3)^0 = X_1 \cdot X_2 \\ Z_3 &= (X_1)^{-1} \cdot (X_2)^0 \cdot (X_3)^1 = X_1^{-1} \cdot X_3 \\ Z_4 &= (X_1)^0 \cdot (X_2)^1 \cdot (X_3)^{-1} = X_2 \cdot X_3^{-1} \end{aligned} \tag{6}$$

Thus, based on the main R-RGP matrix (Eq. (2)), the following equation is obtained:

$$\begin{aligned} Y &= a_0+a_1Z_1+a_2Z_2+a_3Z_3+a_4Z_4 \\ &= a_0+a_1X_1+a_2X_1X_2+a_3X_3/X_1+a_4X_2/X_3 \end{aligned} \tag{7}$$

EPR calculates the adjustable parameters, a_j, using the linear LS method by minimizing the sum of squared errors (SSE) as the cost function. Each exponent in the ES matrix corresponds to a value in the user-defined EX. Accordingly, the symbolic regression problem is transformed into a problem of finding the best ES, i.e., finding the EPR structure using the GA integer number.

As a major output of regression analysis, the coefficient of determination (COD) indicates the proportion of the variance in the dependent variable that can be predicted from the independent variable. COD has been utilized to assess the performance of prediction models. The SSE function is also used to direct the search process toward the best-fit model, and the COD is adopted to measure the accuracy of a proposed model, i.e., the fitness function, as follows:

$$\begin{aligned} COD &= 1 - \frac{\sum_N (Y_a - Y_p)^2}{\sum_N \left(Y_a - \frac{1}{N}\sum_N Y_a\right)^2} \\ SSE &= \frac{\sum_{i=1}^{N} (Y_a - Y_p)^2}{N} \end{aligned} \tag{8}$$

Figure 2 displays a typical schematic of the EPR procedure. Depending on the transfer function selected by the user for the hidden neurons, ANNs are either linear or nonlinear, whereas EPR overcomes this problem and can perform both linear and nonlinear analyses in a single algorithm implementation [11]. Parameter estimation and over-fitting are the disadvantages of ANN models. EPR can overcome the shortcomings of the GP process, such as the number of evolutionary parameters to tune, computational performance, and complexity of the symbolic models [11]. In this study, EPR was adopted to avoid the problems associated with ANNs and GP. To this end, the application of this method in modeling engineering problems was further investigated.

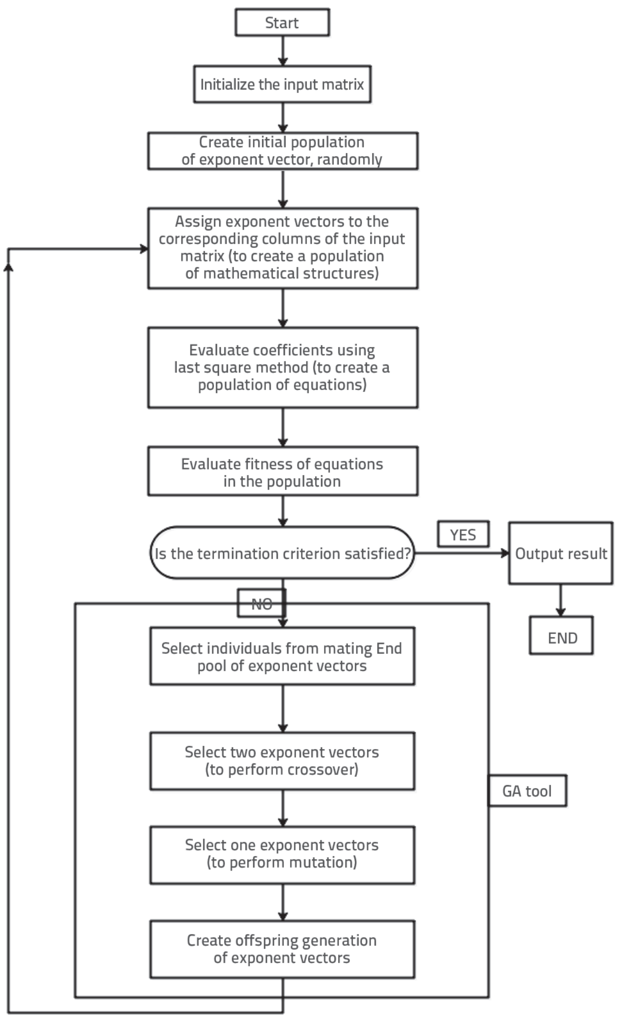

Figure 2. Flow diagram of EPR procedure [12]

3. Application of EPR in modelling engineering problems

The potential of EPR in modelling and analyzing different disciplines of engineering from structural to geotechnical and environmental engineering has been investigated. Ghaboussi et al. [13] first proposed the application of an ANN in material modelling to model concrete behavior. Since then, studies have examined the application of ANNs to other engineering materials, including soils and waste materials.

Bruno et al. [14] first employed an EPR model to evaluate the short-term dynamics of the shoreline on the Ionian coast of the Apulia region. Their results showed that EPR can be used to reliably forecast coastal evolution.

Ahangar-Asr et al. [15] presented the application of EPR for analyzing the stability of soils and rock slopes. They employed an EPR model to predict the safety factors of slopes against failure under conditions not used in the model-building process. The results indicated that the proposed model is highly effective and robust for accurately predicting various aspects of slope behavior.

Rezania et al. [12] employed EPR to assess earthquake-induced soil liquefaction and lateral displacement. It was concluded that the developed models learn the complex relationships of either of these problems and yield their contributing factors in the form of a function with high accuracy (mostly >90 %).

Faramarzi et al. [16] developed an EPR model to predict the behavior of steel plate shear walls (SPSWs) under cyclic behavior. The results showed that the proposed approach can predict the lateral deformation of SPSWs due to cyclic loading.

Ahangar-Asr et al. [17] proposed a novel approach based on EPR-predicted permeability (K), the maximum dry density, and the optimum moisture content of soils as functions of physical properties of soils. They developed EPR models based on the results of experimental tests, including standard proctor, constant-head permeability, and falling-head permeability tests, conducted on soils comprising four components (bentonite, limestone dust, sand, and gravel) mixed in different proportions. A comparison of the findings showed that the developed EPR models are highly accurate and robust in predicting soil permeability and compaction characteristics.

Ahangar-Asr et al. [18] proposed the use of EPR for predicting a soil–water characteristic curve (SWCC). The developed EPR-based model was validated using a database from pressure plate tests performed on clay, silty clay, sandy loam, and loam soils. The results of model predictions were compared with actual data. A parametric study was also conducted to evaluate the effects of contributing parameters on the predictions of the proposed EPR model. It was concluded that the developed EPR model provides very accurate SWCC predictions.

Keramati et al. [19] introduced a primary model based on EPR to predict the strain–stress behavior of solid wastes of the Kahrizak landfill (Iran) under different primary conditions by analyzing large-scale direct shear test results. The findings indicated that the proposed EPR model has considerable potential for estimating the strain–stress behavior of waste materials.

Khoshkroudi et al. [20] developed an EPR model to predict soil saturated water content (SWC) and validated it using three databases. The jackknife cross-validation method was adopted to evaluate the reliability of the pedotransfer functions (PTFs). The PTF provided by EPR with the highest COD and the fewest terms was selected. Their findings clearly showed the robustness of the proposed EPR approach in predicting SWC.
Karimnader-Shalkouhi et al. [21] presented a new approach based on EPR to predict the safety factors of a quay wall against sliding, overturning, and bearing capacity failure as functions of the shear strength parameters, wall geometry, and loading conditions of a soil. The geotechnical properties of the soil, geometric parameters of the wall, and loading conditions were employed to estimate the safety factors of a quay wall in drained and undrained conditions. They compared EPR models with the values in a databank. A comparison of the results demonstrated that the developed models provide predictions with high accuracies of ~95 %.

4. Laboratory test for EPR-based model development

4.1. Material

In this study, the material used in the large-scale oedometer tests to develop EPR models was composed of Anzali sand and HDPE. Anzali (Iran) sand is a poorly graded sand under the Unified Soil Classification System [22]. Previous studies have determined the range of physical characteristics of Anzali sand soil [22] (the first two columns of Table 1). The measured values of the soil parameters used in this research are listed in the last column of Table 1. Tables 2 to 4 list the gradation of the sand, properties of the HDPE chips, and gradation of the HDPE, respectively. The HDPE chips used in the present study were purchased in a shredded form from a recycling factory. In the factory, the HDPE is shredded into small pieces by machine cutters after washing and drying.

Table 1. Physical parameters of Anzali sand

Measured	Maximum	Minimum	Parameter
D50 [mm]	0.21	0.32	0.21
D_{max} [mm]	1.18	2.36	1.18
C_u	1.9	2.5	2.4
C_c	0.83	1.2	1.20
$\gamma_{d\,max}$ [kN/m^3]	15.1	16.9	16.2
$\gamma_{d\,min}$ [kN/m^3]	14	15.8	15
e_{min}	0.57	0.69	0.605
e_{max}	0.69	0.89	0.73
G_s	2.59	2.70	2.65

Table 2. Particle size distribution of sand

Sieve number	Mass passing [%]
No. 4 (4.75 mm)	99.98
No. 8 (2.36 mm)	99.76
No. 16 (1.18 mm)	99.70
No. 30 (0.595 mm)	99.50
No. 50 (0.3 mm)	94.64
No. 100 (0.15 mm)	6.76
No. 200 (0.075 mm)	0
Pan	0

Table 3. HDPE resin properties of geomembranes in geotechnical engineering

Characteristic	Property
Co-monomer	Buten^{-1}, heksan^{-1}, okten^{-1}
Co-monomer fraction	< 10 % by weight
Density	0.932-0.942 g/cm^3
Melt mass flow rate (190/5)	0.3-3 g/10 min
Melting temperature	130°
Crystallinity	50-55 %
Number-average molecular mass, Mn	15000-50000
Polydispersity, Mw/Mn	4-15

Figure 3 shows optical microscopy photos of the Anzali sand and magnified photos of the crushed HDPE.

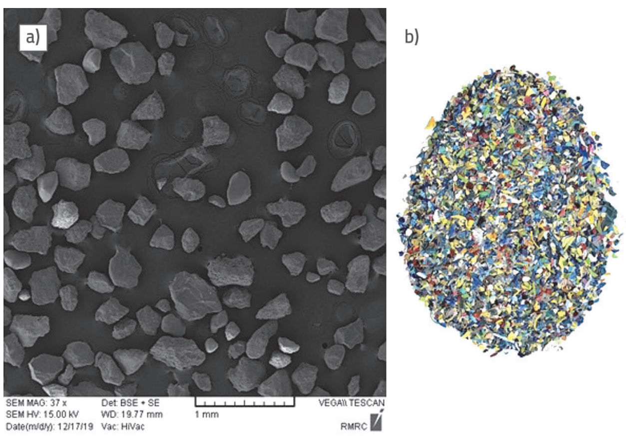

Figure 3. a) Optical microscopy photos of Anzali sand; b) magnified photos of crushed HDPE

Table 4. Particle size distribution of HDPE

Sieve number	Mass passing [%]
No. 4 (4.75 mm)	100
No. 8 (2.36 mm)	99.99
No. 16 (1.18 mm)	42.18
No. 30 (0.595 mm)	11.67
No. 50 (0.3 mm)	2.073
No. 100 (0.15 mm)	0.316
No. 200 (0.075 mm)	0
Pan	0

4.2. Large-scale oedometer test

Large oedometers can overcome the two major problems of the standard-size Casagrande-type oedometer:

- limitation on the maximum particle diameter of a specimen
- limitation on the magnitude of the applied vertical stress.

Moreover, a large specimen probably is highly representative of the field conditions. As a load is applied hydraulically, the loading rate can be carefully controlled to fit the objective of a measurement [23].

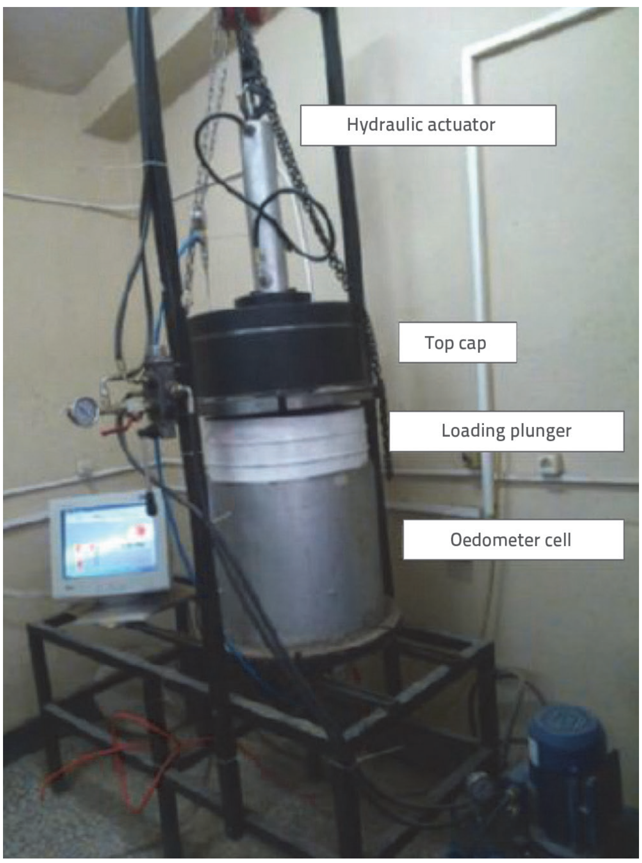

Figure 4. Large oedometer testing apparatus

To measure the compressibility behavior of a mixture of the sand and the HDPE chips under a vertically applied stress, a large cylindrical oedometer was employed. This oedometer had a diameter of 492 mm and a height of 550 mm and was designed, fabricated, and calibrated at the Soil Mechanics Laboratory of the Faculty of Engineering at the University of Guilan (Figure 4). The oedometer consisted of a loading frame, a computer-controlled hydraulic loading plunger, an oedometer cell, displacement, pore pressure, normal and lateral pressure transducers, and a computerized data acquisition system [24]. For conducting tests, five dry mass ratios of the HDPE (0, 2, 4, 6, and 8 % on volumetric basis) were selected and mixed manually with the soil. To avoid segregation during sample preparation, a small amount of water was added to the dry soil for partial wetting, and the HDPE chips were uniformly distributed with the soil. After mixing, the samples were poured into five layers; each layer was molded into the chamber of the large oedometer apparatus, and a hand tamper was employed to compact the layers and reach the target dry density. Relative densities of mixtures of 40 % and 70 % were selected to investigate the soil–HDPE deformation characteristics. Loads were applied sequentially in steps of 100, 200, and 300 kPa. Owing to the combination of soils with five dry mass ratios of the HDPE, two relative densities, and three loads (5 x 2 x 3), 30 series of large oedometer tests were conducted. Vertical displacements and lateral loads were obtained from large-scale oedometer experiments based on the applied loads. Eq. (9) shows that the coefficient of lateral earth pressure, K_0, is defined as the ratio of the horizontal stress, σ_h, to the vertical stress, σ_v, which are obtained from the test results.

$$K_0 = \frac{\sigma_h}{\sigma_v} \tag{9}$$

5. EPR modelling

Three input variables, HDPE content (η), relative density (D_r), and normal stress (σ_v), were used for developing EPR models for the lateral earth pressure coefficient at rest (K_0) and volume compressibility coefficient (m_v) values.

5.1. Modelling for lateral earth pressure coefficient at rest (K_0)

The coefficient of lateral earth pressure, which is a key factor in geotechnical design, is essential to be computed in designing all types of supporting walls, evaluating soil shear resistance and sleeve friction of piles, and interpreting in situ tests. K_0 was found to drastically decrease with the percentage, overburden pressure, and skeletal relative density of the HDPE chips. By raising the overburden pressure or the skeletal relative density, a denser mixture skeleton was produced owing to the compacted mixture. The large-scale oedometer data (K_0, including the data for the samples with and without the HDPE, were utilized to develop EPR models (Figure 5).

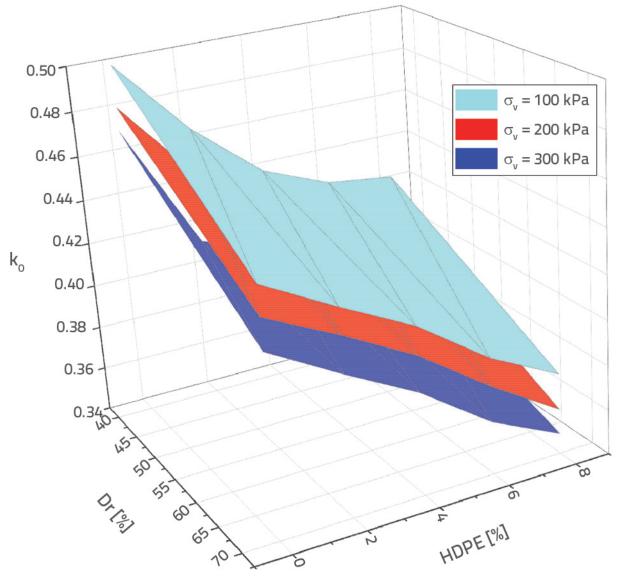

Figure 5. Large-scale oedometer data (K_0) at Dr = 40,70 %, σ_n = 100, 200, and 300 kPa, and η = 0, 2, 4, 6, and 8 %

The results of the coefficients of lateral earth pressure of the mixtures obtained from the large oedometer tests were used to develop EPR models. Based on the COD values, the hyperbolic secant relation was found to better represent the relationship between the input and output parameters than other relations. The relation obtained from EPR is expressed as follows:

$$K_0 = -0.00052409 D_r + 1037925.954 \sigma_v^{0.5} sh(\eta) sh(D_r)^{0.5} - 1.6564e^{-5} \sigma_v D_r^{0.5} - 0.071319 \sigma_v^{2} D_r^2 \cdot sh(D_r)^{0.5} - 0.00012979 \eta \sigma_v + 0.49906 \quad (10)$$

For validation, sensitivity analyses were conducted to examine the generalization ability (robustness) of the EPR models in deducing the underlying physical relevance of the problems and to investigate the significance of the model inputs. To this end, one variable was changed and all other variables were fixed to the mean values, and accordingly its effects on K_0 and m_v was investigated. Synthetic data were generated by raising their values by a percentage of the total minimum–maximum range. Subsequently, these input values were inputted into the EPR models and the corresponding outputs were obtained. This process was iteratively performed for the next input variable until the responses of the models were checked for all inputs. Following this, the model robustness was assessed by investigating the conformation of the predicted outputs to the existing experimental results.

Figure 6 shows a comparison of the results of the best-developed EPR model and the experimental data. The horizontal and vertical axes represent the lateral pressure coefficient measured from the oedometer test and calculated from the EPR formula (Eq. (9)), respectively. Eq. (11) expresses the relationship between the laboratory and EPR results. Eq. (11) and Figure 6 show that the developed EPR model presents excellent performance.

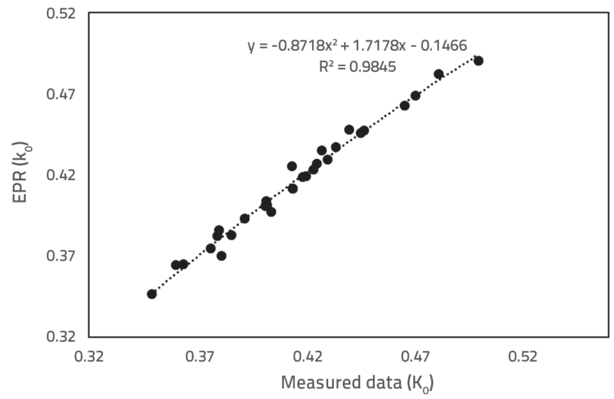

Figure 6. Comparison of measured and predicted performance for lateral earth pressures of HDPE–sand mixtures from large-scale oedometer tests

$$EPR(K_0) = -0{,}8718\,[\text{measured }(K_0)]^2 + 1{,}7178\,[\text{measured }(K_0)] - 0{,}1466 \quad (11)$$

The effects of parameters Dr, h(%), and s_v on K_0 and mv were investigated. As previously mentioned, the tests were performed on 30 samples with 2 relative densities (40 % and 70 %), 5 percentages of HDPE chips (0, 2, 4, 6, and 8 %), and three pressures (100, 200, and 300 kPa). Figure 7 illustrates the results of the parametric study on the effect of altering (D_r, η(%) and σ_v) separately on K_0. As predicted by the proposed best-developed model and shown in Figure 7.a (five points: 0, 2, 4, 6, 8 %), increasing the percentage of the HDPE chips reduces the lateral earth pressure coefficient at rest (K_0) owing to the elastic deformability of the HDPE. Higher relative density and structural rigidity lead to a smaller K_0 value owing to the increased

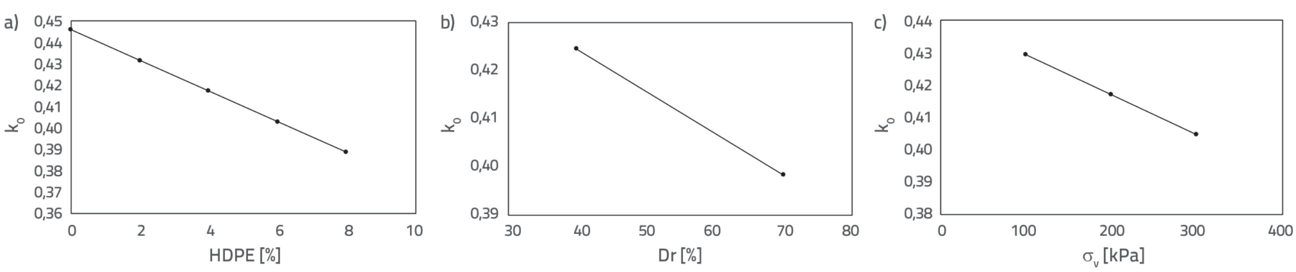

Figure 7. Parametric study results for lateral earth pressure coefficient at rest (K_0)

interaction between the sand particles and densification (Figure 7.b, two points: 40 and 70 %). For a higher overburden pressure, the rigidity is increased owing to the compressed HDPE and sand skeleton; consequently, the value of K_0 is lower at higher stresses (Figure 8.c, three points: 100, 200, 300 kPa).

Increasing the relative density of the HDPE–soil mixture decreases the lateral earth pressure coefficient of the mixture, which is similar to the effect of raising the relative density on the lateral earth pressure coefficients of pure sand and sand–tire mixtures reported by Jamshidi et al. [25].

5.2. Modelling for volume compressibility coefficient (m_v)

When soils are subjected to uniform loading over large areas such as fills, embankments, and wide foundations, their compressibility characteristics are typically important. The compressibility of soils under one-dimensional compression can be described based on the decrease in the volume of voids with increasing effective stress. The large-scale oedometer data (m_v), including the data for the samples with and without the HDPE, were utilized to develop EPR models (Figure 8).

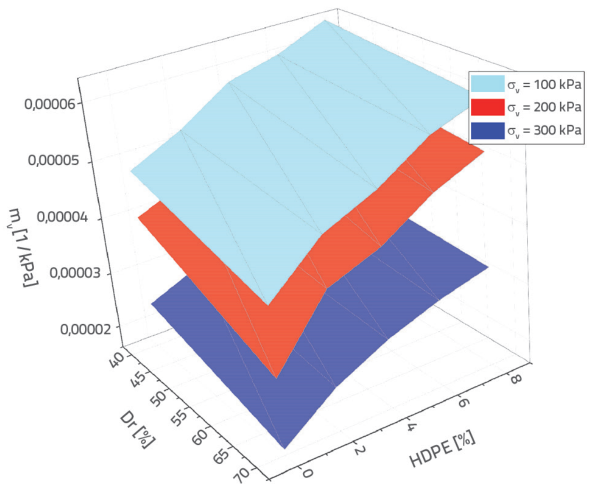

Figure 8. Large-scale oedometer data (m_v) with Dr = 40,70 %, σ_n = 100, 200, and 300 kPa, and η = 0, 2, 4, 6, and 8 %

Based on Figure 8, the volume compressibility coefficient of a HDPE chips–sand mixture depends on its equivalent rigidity, which is influenced by the percentage of the HDPE chips, overburden pressure, and skeletal relative density. Owing to the low rigidity of the HDPE, greater deformability and compressibility are expected. However, the skeletal relative density and the overburden pressure act similarly. The results in Figure 8 show that increasing the overburden pressure raise the skeletal relative density, cause a denser sand skeleton, and induce densification in the mixture; consequently, the volume compressibility coefficient decreases with the overburden pressure.

The experimental results for the volume compressibility coefficients (m_v) of the mixtures for different parameters (η, D_r, σ_v) were considered to develop EPR models. Based on the COD, simplicity, and robustness values of the relations, that for predicting the volume compressibility coefficient of a soil–HDPE mixture was selected.

$$m_v = -2,4054\times10^{-9}D_r - 2,9893\times10^{-10}\,\sigma_v^2 + 6,5281\times10^{-8}\eta D_r + 1,4821\times10^{-9}\eta\sigma_v - 4,2942\times10^{-11}\eta\sigma_v^2 + 5,4733\times10^{-5} \quad (12)$$

Figure 9 shows the comparison of the results of the best-developed EPR model and the experimental data. The horizontal and vertical axes represent the volume compressibility coefficient measured from the oedometer test and that calculated from the EPR formula, respectively.

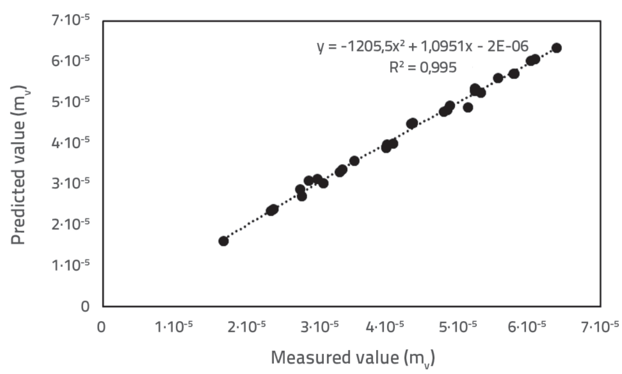

Figure 9. Comparison of measured and predicted performance for volume compressibility coefficients of HDPE–sand mixtures from large-scale oedometer tests

The following equation expresses the relationship between the laboratory and EPR results, which shows that the developed EPR model presents excellent performance.

$$EPR(m_v) = -1205,5\,[\text{measured } (m_v)]^2 + 1,0951\,[\text{measured } (m_v)] - 2\times10^{-6} \quad (13)$$

The results of the parametric study shown in Figure 10.a indicate that raising the percentage of the HDPE chips

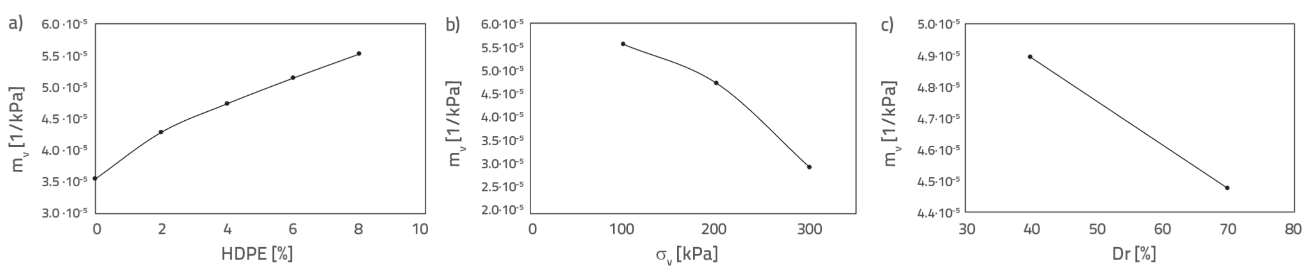

Figure 10. Parametric study results for volume compressibility coefficient (m_v)

nonlinearly increases the volume compressibility coefficient (m_v). Moreover, increasing the skeletal relative density and overburden pressure, in order, result in a linear and nonlinear decrease in the volume compressibility coefficient (Figures 10 b, 10.c), which is consistent with the experimental findings.

6. Conclusion

Presently, increasing the capacity of plastic waste disposal is one of the major challenges worldwide. To reduce the demand for landfill space, the current research investigated plastic waste reuse by large oedometer tests in civil engineering and developed EPR models for estimating the deformation characteristics of a soil mixed with HDPE. The large oedometer has overcome the two major limitations of the standard-size Casagrande-type oedometer: limitation on the maximum particle diameter of the specimen and limitation on the magnitude of the applied vertical stress. EPR was applied to obtain the relationship between the lateral earth pressure coefficient at rest and the volume compressibility coefficient with the HDPE content (η), relative density (D_r), and normal stress (σ_v). The EPR technique provided reasonable and robust predictions of the volume compressibility coefficient and the lateral earth pressure coefficient at rest with good accuracy compared to the laboratory results for HDPE–sand mixtures. These findings show that in addition to being the optimal approach to solve the problem of insufficient plastic waste disposal, HDPE–sand mixtures can be used to retain wall backfills owing to the lower K_0 content needs.

REFERENCES

[1] Ackerman, F.: Waste management and climate change, Local Environment, 5 (2000) 2, pp. 223–229

[2] United States Environmental Protection Agency: Understanding global warming potentials, Greenhouse gas emissions, https://www.epa.gov/ghgemissions/understanding-global-warming-potentials, 15.9.2021.

[3] Singh, N., Hui, D., Singh, R., Ahuja, I.P.S., Feo, L., Fraternali, F.: Recycling of plastic solid waste: A state of art review and future applications, Composites Part B 2016, (2017), pp. 409-422

[4] Choudhary, A.K., Jha, J.N., Gill, K.S.: Utilization of plastic wastes for improving the sub-grades in flexible pavements, GeoShanghai International Conference, 2010., pp. 320-326

[5] Kalumba, D., Chebet, F.C.: Utilisation of polyethylene (plastic) shopping bags waste for soil improvement in sandy soils, Proceedings of the 18th International Conference on Soil Mechanics and Geotechnical Engineering, Paris, 2013.

[6] Kumar, T., Panda, S., Hameed, S., Maity, J.: Behaviour of soil by mixing of plastic strips, International Research Journal of Engineering and Technology (IRJET), 5 (2018), pp. 2578-2581

[7] Rakic, D., Basaric, I., Caki, L., Coric, S.: Contribution to the geotechnical classification of municipal waste landfills in Serbia, Environmental Geotechnics, 7 (2020) 7, pp. 501–511

[8] Abukhettala, M., Fall, M.: Geotechnical characterization of plastic waste materials in pavement subgrade applications, Transportation Geotechnics, 27 (2021), 100472.

[9] Aswad, Hassan, H.J., Rasul, J., Samin, M.: Effects of plastic waste materials on geotechnical properties of clayey soil, Transportation Infrastructure Geotechnology, (2021) 8, pp. 391-413

[10] Giustolisi, O., Savic, D.A.: Advances in data-driven analyses and modelling using EPR-MOGA, Journal of Hydroinformatics, (2009), pp. 225-236

[11] Giustolisi, O., Savic, D.A.: A Symbolic Data-driven technique based on evolutionary polynomial regression, Journal of Hydroinformatics, 3 (2006) 8 , pp. 207-222

[12] Rezania, M., Faramarzi, A., Javadi, A.A.: An evolutionary based approach for assessment of earthquake-induced soil liquefaction and lateral displacement, Eng. Appl. Artif. Intell., 24 (2011) 1, pp. 142–153, DOI: https://doi.org/10.1016/j.engappai.2010.09.010

[13] Ghaboussi, J., Garret, J.H, Wu, X.: Knowledge-based modelling of material behaviour with neural networks, Journal of Engineering Mechanics Division, 117 (1991) 1, pp.153–164

[14] Bruno, D.E., Barca, E., Goncalves, M., Passarella, G.: Evolutionary polynomial regression model for the prediction of coastal dynamics, 6th EnvImeko – IMEKO TC19 – Second Edition, 2016., pp. 6-11

[15] Ahangar-Asr, A., Faramarzi, A., Javadi, A.: A new approach for prediction of the stability of soil and rock slopes, Engineering Computations, 27 (2010) 7, pp. 878-93

[16] Faramarzi, A., Mehravar, M., Veladi, H., Javadi, A.A., Ahangar-Asr, A., Mehravar, M.: A hysteretic model for steel plate shear walls, Proceedings of the 19th ACME Conference, Edinburgh, Heriot-Watt University, 2011.

[17] Ahangar-Asr, A., Faramarzi, A., Mottaghifard, N., Javadi, A.A.: Modeling of permeability and compaction characteristics of soils using evolutionary polynomial regression, Computers & Geosciences, 37 (2011) 11, pp. 1860–1869

[18] Ahangar-Asr, A., Johari, A., Javadi, A.A.: An evolutionary approach to modelling the soil–water characteristic curve in unsaturated soils, Computers & Geosciences, 43 (2012), pp. 25–33

[19] Keramati, M., Sina Khodabakhsh Reshad, S., Asgarpour, S., Tutunchian, M.A.: Predicting shear strength of municipal waste material by evolutionary polynomial regression (EPR), EJGE, (2014), pp. 53-69

[20] Salehi-Khoshkroudi, S., Gholami, M., Ziatabar, M., Ramezani, M.: Prediction of soil saturated water content using evolutionary polynomial regression (EPR), Archives of Agronomy and Soil Science, 60 (2014) 8, pp. 1155-1171

[21] Karimnader-Shalkouhi, S., Karimpour-Fard, M., Lashteh Neshaei, M.A.: Evolutionary polynomial regression-based models to estimate stability of gravity hunched back quay walls, AUT Journal of Civil Engineering, 2 (2018) 1, pp. 79-86

[22] Arabani, M., Pedram, M.: Laboratory investigation of rutting and fatigue in glassphalt containing waste plastic bottles, Construction and building materials, (2016), pp. 378-383

[23] Terzaghi, K.: Theoretical Soil Mechanics, John Wiley & Sons, NewYork, 1943.

[24] Mokhtari, M., Shariatmadari, N., Heshmati, A., Salehzadeh, H.: Design and fabrication of a large-scale oedometer, Journal of Central South University, (2015), pp. 931-936

[25] Jamshidi Chenari, R., Alaie, R., Fatahi, B.: Constrained compression models for tire-derived aggregate-sand mixtures using enhanced large scale oedometer testing apparatus, Geotechnical and Geological Engineering, 37 (2019), pp. 2591–2610