Transportation Infrastructure Geotechnology (2022) 9:835–853
https://doi.org/10.1007/s40515-021-00199-y

TECHNICAL PAPER

Shrinkage Limit Multi-AI-Based Predictive Models for Sustainable Utilization of Activated Rice Husk Ash for Treating Expansive Pavement Subgrade

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Accepted: 5 September 2021 / Published online: 27 September 2021

Abstract

Swell-shrink phenomenon experienced by foundation soils like the subgrade layer is a major cause of failures in pavement facilities. This phenomenon is fundamentally caused by rise in water table and moisture ingress from runoff, and through pavement surface cracks and lateral movement of water from location to location. Repeated laboratory trails prior to design and construction can actually be avoided by using soft computing–based predictive models to propose model expressions, which can be used during the design stage and subsequently to monitor the behavior and performance of the structure. This research utilized the intelligent abilities of genetic programming (GP), artificial neural network (ANN) and genetic algorithm (GA), and optimized polynomial linear regression (PLR) known as the evolutionary polynomial regression (EPR) to forecast the shrinkage limit of expansive soil treated with rice husk ash (RHA) and different quicklime dosage–activated rice husk ash. At the end of prediction, performance indices, i.e., R^2 and SSE, were used to test the accuracy of the models. It was observed that EPR outclassed ANN and GP with indices of 0.974 and 1.4%, respectively. Meanwhile, the composites of RHA showed significant improvement on the shrinkage limit of the treated soil for use as a compacted subgrade material.

Keywords Pavement subgrade · Expansive soil · Quicklime-activated rice husk ash (QARHA) · Genetic programming (GP) · Artificial neural network (ANN) and evolutionary polynomial regression (EPR) · Swell-shrink cycle (SSC)

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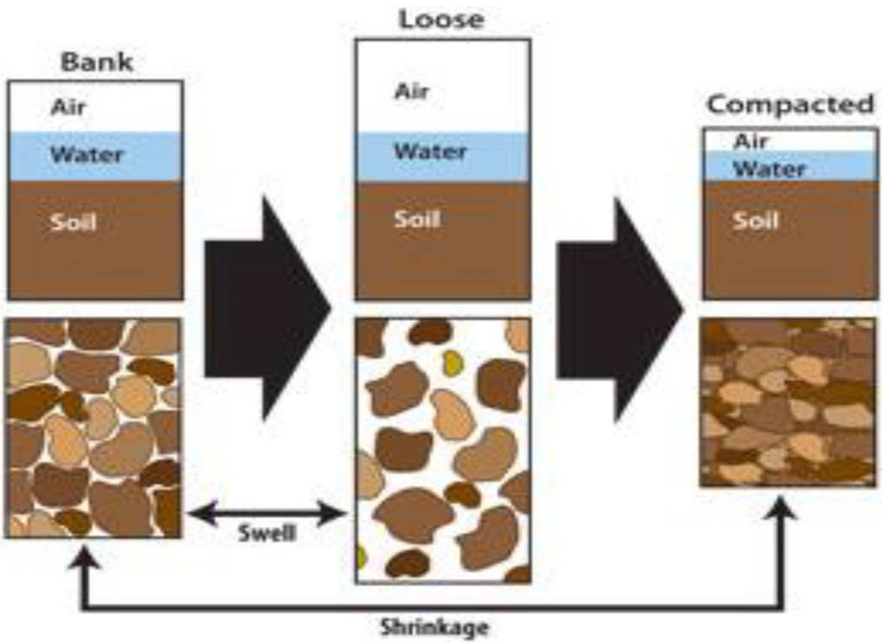

Fig. 1 Visual illustration of volume changes in expansive soils (Onyelowe et al. 2021c)

1 Introduction

1.1 Preamble

Pavement design and its associated behavior can be problematic depending on the criticality of change in its moisture content leading to remarkable change in volume which could translate to uneven pavement resulting from sinking down or heaving up of overlying layers (Chen 1988; Onyelowe et al. 2020). As subgrade remains the in situ material upon which the pavement structure is placed, there is need to look at pavement performance not just in terms of pavement structure and mix design alone, but in terms of the volume change and crack development within the subgrade (Chen 1988; Onyelowe et al. 2020). Being a measure of the average oven-dry length of the sample after shrinkage to the original length which occurs at an initial water content at or above the liquid limit, soil shrinkage which generally yields shrinkage cracking and/or reduction in overall volume (Onyelowe et al. 2020; Chen 1988; also see Fig. 1) affects the functionality of compacted soils in geotechnical and geoenvironmental engineering applications (Julina and Thyagaraj 2018; Al-Dakheeli and Bulut 2018). Soil shrinkage can generally be induced or influenced by various phenomena such as evaporation from soil surface, lowering of groundwater table, and decrease in soil moisture in a swell-shrink cycle (SSC) leading to ultimate cracking of the ground surface (Azadegan et al. 2012, etc.).

The drying process enables the successful tracking of shrinkage cracks and strain, even as the crack keeps building in width until the water content hits the shrinkage limit (Onyelowe et al. 2020, 2021c). As the moisture content lowers, increased surface tension instigates capillary stress within the void space. Owing to this phenomenon, an adjustment of the surface appearance is initiated just as the surface menisci journeys below the soil surface. Expansive subgrade types are one of the main causes of damage to road network across many cities in Nigeria and even beyond. Little wonder that care must be taken when designing pavement to ensure that the critical influencers of pavement stability and durability are adequately met. For instance, the subgrade upon which the pavement will be placed usually has a remarkable effect on the overall stability of the pavement. In addition, the subgrade stiffness and drainage characteristics all play integral roles in assigning the most practicable pavement layer thickness. All these parameters are so interconnected that appropriate analysis and evaluation become imperative (Chaney et al. 1998). Complexities in design and assigning of soil design parameters such as shrinkage limit are intensified when the exact expected traffic loading along a proposed pavement is unknown. In consequence, accurate determination of traffic loading is necessary for the estimation of pavement composition, layer type, and thickness of the pavement. Generally, based on the degree of environmental friendliness or harshness such as extreme temperature and ice formation, there could be significant impacts on the overall pavement performance and longevity. The application of stabilization materials such as rice husk ash (RHA) in enhancing subgrade performance and generally soil properties has gained strong impetus prior to the birth of this decade. To illustrate, Onyelowe et al. (2021c) evaluated and conducted shrinkage limits and index test results on an expansive soil treated with RHA and progressive percentage addition of quicklime activated rice husk ash (QARHA) obtained using laboratory testing procedure; they however concluded that an increase in the rate of activation of rice husk ash with quicklime gave a higher pozzolanic response.

1.2 Use of Nanotextured Materials and Green Composites such as Rice Husk Ash for Enhancement of Soil Properties such as Shrinkage Properties

The use of green composites and various ash binders has proven a vital and sustainable energy and environmentally friendly option for geotechnical engineers. As pavement soil moisture content decreases owing to its evaporation into the surrounding environment, there is resultant cracking of the ground surface. The incorporation of the nanotextured materials like rice husk ash (RHA) and lime enhances the soil matrix for improved performance when employed for pavement works, and also aids in proper waste disposal. RHA, a by-product of rice milling, has gained vast usage as a soil stabilizer and an alternative to the final disposition with environmental benefits. Al-Taiea et al. (2016) employed lime stabilization to reduce the swell-shrink tendency of soils used for pavement construction and thus reduce the possible damage. After their stabilization and compaction exercise, the subgrade was naturally exposed to cycles of full swell and or partial shrinkage due to climatic cycles. Al-Dakheeli and Bulut (2018) performed restrained shrinkage tests for expansive soils compacted close to the optimum moisture content and subjected to the air-drying. Their evaluation was based on the restrained ring testing method, while they evaluated the volume change for all the tests using digital image processing technique. Their experiment revealed that for all the tested specimens, a single crack initiates at the inner face of the circular-hole specimens and grows toward the exterior edge. Moreover, their analysis further showed that based on the soil shrinkage curve that crack initiation occurs after the soil specimens attain the normal shrinkage and initiates the residual shrinkage stage.

Various reports have been made relating to the behavior and response of soil shrinkage limit to several geotechnical parameters. For instance, Sridharan and Prakash (2000) remarked that the shrinkage limit of a natural soil does not depend upon plasticity characteristics, and it is primarily governed by the relative grain size distribution of the soil. Shrinkage limit is a notable technique for identification and classification of soil, and can be related with various properties such as surface area, cation exchange capacity, mineralogical and geological history, swelling behavior, California bearing ratio, shear strength, compaction characteristics, and many more (Wroth and Wood 2011).

1.3 Evolutionary Computational Techniques for Predicting Soil Parameters such as Shrinkage Limit

For a more technical and real-life behavioral modeling, a nonlinear mathematical model can be used to analyze and interpret the complex behavior and response of a number of geotechnical parameters without revisiting the tedious experimental procedures. One sure promising option for this is the use of machine learning approaches for analyzing and optimizing nonlinear systems in complex geometries (Dao 2011; Ebid 2004). A system that uses its metaheuristic or stochastic optimization property to predict parameters and solve problems based on an iteratively configured and robust trial and error processes is worthwhile. Being a biological evolution template like the Darwanian struggle for survival, evolutionary computation techniques consistently evolve as variants of artificial intelligence such as differential evolution (DE), self-organizing migrating algorithm (SOMA), genetic algorithm (GA), genetic programming, artificial neural networks, simulated annealing (SA), and support vector machine (SVM), and many other simple and hybrid models have gained deeper applications in predicting soil parameters such as shrinkage limit, consistency limits, and shear strength parameters (Demir 2005, 2008, etc.).

Meanwhile, artificial neural networks, being forecasting methods that are based on simple mathematical models of the brain that allow complex nonlinear relationships between the response variable and its predictors, have been largely employed in predicting simple and complex soil parameters like shrinkage limit (Ellis et al. 1992; Cheng and Shi 2020). Lyes and Buyle-Bodin (2013) adopted the nonparametric approach of evolutionary computation, artificial neural network (ANN), in order to appropriately predict dimensional variations due to drying shrinkage. Their technique allowed for the development of models for predicting shrinkage. Their models were based on the multilayer back propagation that depended on a very large database of experimental results issued from literature and an appropriate choice of architecture and learning processes. Ikizler et al. (2010) studied the swelling behavior of expansive soil by employing ANN models. They therefore developed prediction model of transmitted lateral swelling pressure, and vertical swelling pressures on a retaining structure based on artificial neural network (ANN) models. Maher et al. (2018) described and discussed descriptive analytics, inquisitive analytics, and predictive analytics that generated insights and inferences based on the experimental dataset developed in their project using multiple linear regressions (MLR), artificial neural networks (ANNs), and support vector regression (SVR) techniques. In the same light, robust variants of genetic programming, namely linear genetic programming (LGP), and a hybrid search algorithm coupling LGP and simulated annealing (SA), called LGP/SA, were employed to predict performance characteristics of stabilized soil. Rezania and Akbar (2007) developed a new genetic programming (GP) approach for predicting settlement of shallow foundations. The GP model which they developed was verified using a large database of standard penetration test (SPT)–based case histories that involved measured settlements of shallow foundations. Trivedi et al. formulated a model based on genetic algorithm which could be used to predict variation in the values of CBR of the sub-grade soil with the addition of a specific percentage of fly ash. The input values for their study were liquid limit (LL), plasticity index (PI), optimum moisture content (OMC), and fraction of fly ash added (F.A. in %), which fundamentally influenced the CBR values. Mohamad et al. developed an evolutionary polynomial regression (ERP), a hybrid genetic algorithm (GA), optimized by artificial neural network (ANN) to predict ripping production outputs, while reporting a superiority of the EPR model over ANN model. Many other studies employing GP models, the ultimate system that searches for an optimal or at least appropriate program among the space of all programs to solve a given inputted problem, have also been reported (Johari et al. 2006; Onyelowe et al. 2021a; Alavi et al. 2011, etc.). The shrinkage limit is not usually tested due to difficulties associated with its interaction with other soil properties and moisture effects. Therefore, evolutionary computational techniques are no doubt, promising systems to predict and analyze it. Despite foregoing researches adopting the use of evolutionary techniques, neither reports on the shrinkage limit that is predicted from critical input parameters affecting it, nor employing multiple deep learning approaches for pavement purposes, has been so far made. For sustainable pavement subgrade utilization, the present study has explored the potentials of the use of GP, ANN, and EPR techniques in predicting the shrinkage limit (W_S) of composites of RHA-treated lateritic soils using predictor parameters as treatment dosage (P), plasticity index (I_P), liquid limit (W_L), plastic limit (W_P), and shrinkage index (I_s).

1.4 Sustainability of Utilizing Activated Rice Husk Ash for Treating Expansive Pavement Subgrade

RHA is produced from the calcination of rice husk (RH) which is an agro-waste obtained from rice farms. Sustainable materials are materials that could be used by the present generation to meet their needs without affecting the ability of future generations to meet their own needs (Obianyo et al. 2021). Low embodied energy (EE) is used for the calcination of agro-waste materials such as RH to generate pozzolanic construction materials unlike the huge EE used for the production of conventional materials like cement (Obianyo et al. 2020a, b). The sustainability of RHA depends on the advantages derived from converting RH agro-waste to useful building materials (RHA) as well as the use of lower EE for the production of RHA. In other words, using activated RHA for the treatment of expansive pavement subgrade in place of the conventional building materials is very sustainable, hence the engineering justification to utilize rice husk ash and its composites formulations as supplementary cementing materials.

1.5 Sustainability of Machine Learning–Based Predictive Models for Pavement Subgrade Design and Performance Analysis

In the sustainability of materials and system, the cost is a vital parameter to consider. Experimental procedures in civil engineering could be time, energy, and resource consuming (Obianyo et al. 2020a, b, 2021), and so, there is a need to develop good models that will be capable of predicting the performance of civil engineering materials. Some of the predictive models that have been used to design and analyze the performance of building and construction materials include Scheffe's simplex model (Onyelowe et al. 2019); non-linear and mixed models (Jin and Chen 2018); multiple regression models (Jaritngam et al. 2013); ANN and support vector machine (Mahamat et al. 2021); and multivariate regression models (Obianyo et al. 2020a, b). The utilization of RHA, which is an unconventional construction material, has the challenge of an inexact understanding of the material properties. These inexactitudes in the understanding of the materials' properties of unconventional construction materials such as RHA are due to the use of conventional material procedures for the determination of their materials' properties (Mahamat et al. 2021). Application of different machine learning–based predictive models such as support vector machine, linear regression, GP, ANN, EPR, and several other techniques for the analysis of the performance of these unconventional materials for building and road pavement construction is vital to mitigate the challenges of conducting repeated experimental procedures for obtaining the properties of materials (Onyelowe and Shakeri 2021). These developed models are sustainable because they save time, energy, and resources that would have been used for recurrent experimental procedures aimed at obtaining the performance of civil engineering materials being utilized for pavement subgrade design and maintenance purposes.

On a general note, it is sustainable to predict pavement subgrade and its associated problems when constructed with erratic and problematic swell-shrink-prone soil with intelligent techniques like genetic programming, artificial neural network, and evolutionary polynomial regression, which saves time and cost of repeated laboratory tests. It is equally sustainable to utilize nonconventional supplementary cementing materials (SCMs) as problematic soil stabilizers in the construction of pavement subgrade.

2 Methodology

2.1 Data Collection

The clayey soil used for this research work was collected from Ndoro Oboro, Abia State borrow pit, the map location of which is presented in Fig. 2. The soil was prepared in accordance with British Standard International BS1377 (1990) basic requirements and stored for the laboratory work at room temperature. Also, the treated soil, which was mixed with quicklime-activated rice husk ash (QARHA), was prepared in line with British Standard International BS1924 (1990).

The quicklime (CaO) used for the activation of RHA had the following properties "whitish water-soluble caustic material with a melting point of 2613 °C, boiling point of 2850 °C, density of 3.34 g/cm^3 and pH of 12.4, cubic halite structure, crystalline solid at room temperature, obtained from the burning of limestone, dissociates into the ions of calcium and oxygen, has abundant supply of calcium for calcination and pozzolanic reaction with clayey soil dipole minerals, forms hydrated lime in aqueous solution, and has indeterminate pH due to transition speed." From the pozzolanic requirement of ASTM C618 (2019) and BS 8615–1 (2019), CaO possesses cementing properties. According to Onyelowe et al. (2021c), "the RHA was derived from the direct combustion of rice husk collected from rice mills in

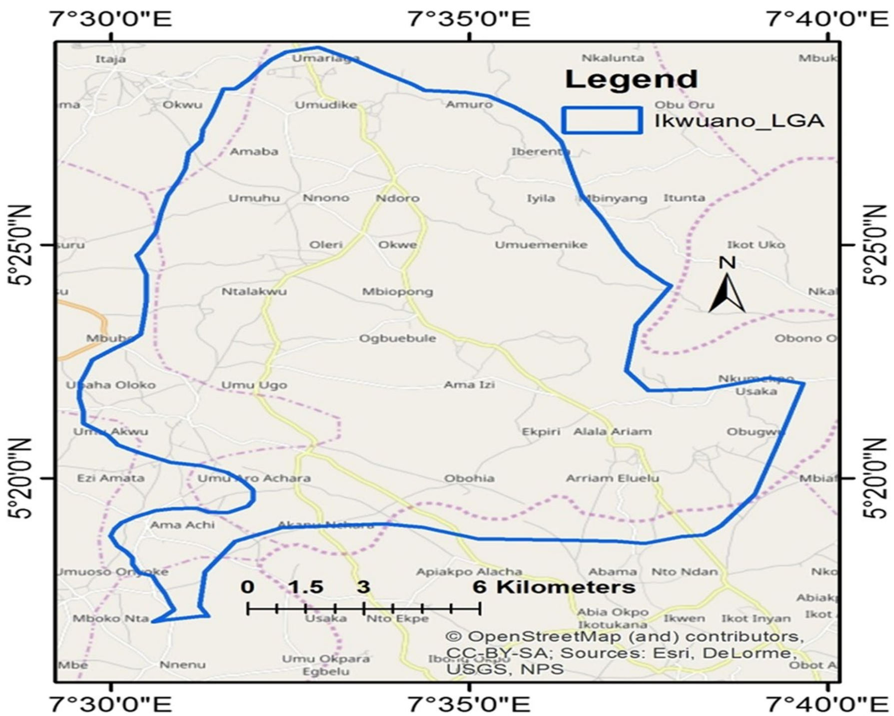

Fig. 2 Soil sample location map

Abakaliki, Nigeria. The ash according to studies satisfies the requirements of a pozzolanic material in accordance with British Standard International BS 8615–1 (2019) and American Standard for Testing and Materials ASTM C618 (2019) due to the presence of Al_2O_3, SiO_2 and Fe_2O_3 in its chemical oxides' composition. The release of silica and alumina from the activated rice husk ash triggers pozzolanic reaction in the clayey soil adsorbed complex interface through hydration and calcination."

2.2 Collected Database; Statistical Analysis

The selected parameters for this predictive model exercise were selected in line with the requirements of Pallant (2013) on reliability and internal consistency of input parameters on intelligent model operations. Forty-one soil samples (1 control and 40 treated specimens) were tested to determine the following physical and mechanical proprieties of RHA, 5%-, 10%-, and 15%-QARHA treatment dosages (*P*, %), mixed with soil at the rate of 1%, 2%, 3%, to 10% for each composite additive as shown in the supplementary material:

- Plastic limit (W_p) %
- Liquid limit (W_L) %
- Shrinkage limit (W_S) %

The measured records were divided into 63% training set (26 records) and 37% validation set (15 records). Table 1 includes the complete dataset, while Tables 2 and 3 summarize their statistical characteristics and the Pearson correlation matrix. From the correlation matrix, it can be deduced that *P* has the highest correlation with the output parameter, W_S more than the W_P and W_L. This shows that *P* has the highest ability to influence the behavior of the shrinkage limit of the soil and the outcome of the model. Finally, Fig. 3 shows the histograms for both inputs and outputs.

3 Research Program

Three different artificial intelligent (AI) techniques were used to predict the shrinkage limit of the tested soil samples. These techniques are genetic programming (GP), artificial neural network (ANN), and polynomial linear regression optimized using genetic algorithm which is known as evolutionary polynomial regression (EPR). All the three developed models were used to predict the values of shrinkage limit (W_S) using the measured treatment dosage (*P*), plastic limit (W_p), and liquid limit (W_L). Each model of the three developed models was based on different approach (evolutionary approach for GP, mimicking biological neurons for ANN, and optimized mathematical regression technique for EPR). However, for all developed models, prediction accuracy was evaluated in terms of sum of squared errors (SSE).

Table 1 The total shuffled and used database

P (%)	W_L (%)	W_P (%)	W_S (%)
Training set			
6	52	33	14.8
4	62	38	13.9
5	59	35.4	14.3
8	41	24	15.9
7	45	27	15.6
4	61	39	14.1
1	71.5	42	13.1
10	61	31	15.6
6	74	40	14.5
3	66	39	14.1
8	68	36	15
4	60	39	14.3
2	71	40	13.2
5	56	37	14.3
10	32	17	16.8
5	54	37	14.5
8	43	25	15.8
9	65	34	15.3
7	49.5	27	15.3
3	81	43.4	13.1
6	54	32	14.8
3	67.4	40	13.7
7	72	37.5	15.3
2	73	41	13.1
9	38	21	16.1
5	77	41.8	14.2
Validation set			
10	33	17	16.5
3	71	40	13.4
2	83	45	12.9
1	74	41.5	12.1
9	36	20	16.2
1	75	41	12.2
2	75	42	13
0	85	47	12.2
7	48	29	15.4
6	50	31	14.9
8	46	24	15.7
9	41.6	22	16.1
10	35	19	16.4
1	83.5	46.5	12.4
4	79	43	13.7

Table 2 Statistical analysis of collected database

	Treatment dosage (P) %	Plastic limit (W_p) %	Liquid limit (W_L) %	Shrinkage limit (W_S) %
Training set				
Max	1.00	32.00	17.00	13.10
Min	10.00	81.00	43.40	16.80
Avg	5.65	59.75	34.50	14.64
SD	2.50	12.53	6.91	0.98
Var	0.44	0.21	0.20	0.07
Validation set				
Max	0.00	33.00	17.00	12.10
Min	10.00	85.00	47.00	16.50
Avg	4.87	61.01	33.87	14.21
SD	3.58	19.20	10.71	1.67
Var	0.73	0.31	0.32	0.12

Table 3 Pearson correlation matrix of input and output parameters

	P	W_L	W_p	W_S
P	1			
W_L	−0.80771	1		
W_p	−0.88016	0.961022	1	
W_S	0.970809	−0.88281	−0.91879	1

The following section discusses the results of each model. The accuracies of developed models were evaluated by comparing the SSE between predicted and calculated shrinkage limit (W_S) values. The results of all developed models are summarized in Table 5.

4 Results and Discussion

4.1 Preliminary Results

According to Onyelowe et al. (2021c), the treatment experiments followed the conditions of ASTM D4318-17e1 (2017), ASTM D4829-19 (2019), and ASTM D4943-18 (2018) to determine the effects of rice husk ash; 5%-, 10%-, and 15%-quicklime activated rice husk (5%-, 10%-, and 15%-QARHA) on the liquid limits; plastic limits; plasticity; linear shrinkage; and shrinkage limit of the treated soil. The multiple data points were collected from the outcome of this research work (Onyelowe et al. 2021c) and subjected to intelligent prediction exercise toward solving pavement subgrade problems.

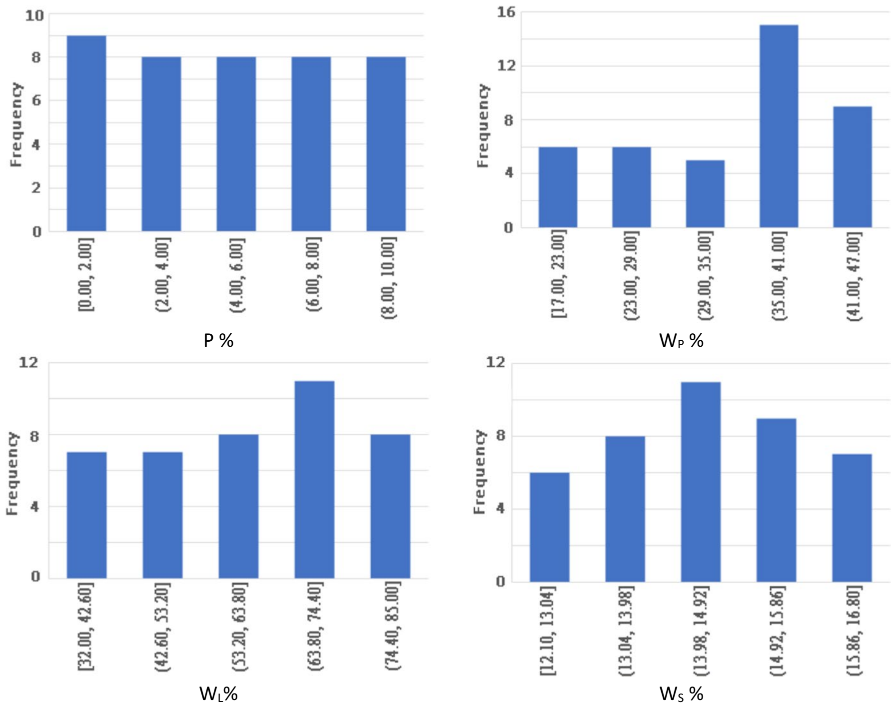

Fig. 3 Distribution histograms for inputs, P, W_P, and W_L and output W_S

The materials' characterization procedure showed that the soil has 45% of its particles passing 0.075-mm sieve, with liquid limit of 66%, plastic limit of 32%, and plasticity index of 34% and with 14% NMC as presented in Fig. 4. The above

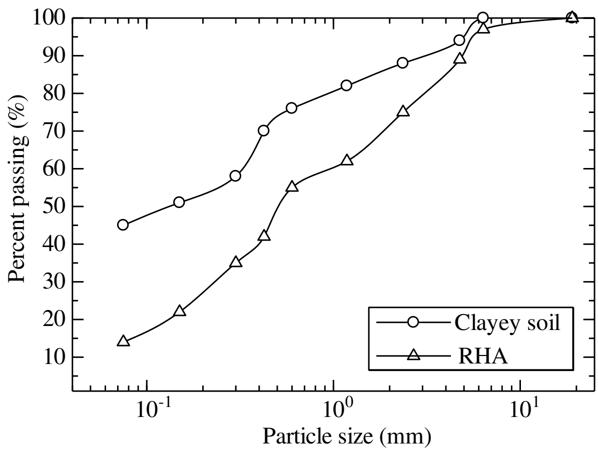

Fig. 4 Particle size distribution curve of the clayey soil and rice husk ash (Onyelowe et al. 2021c)

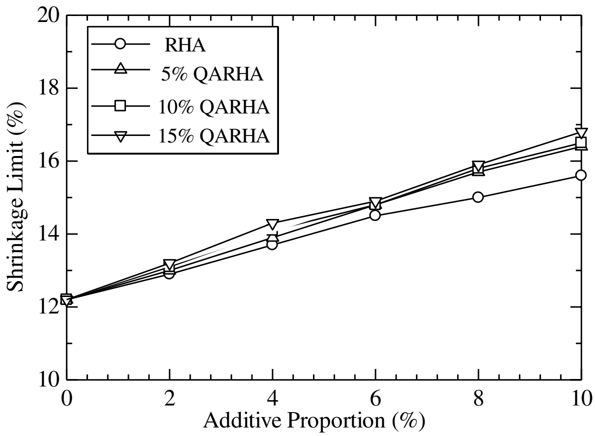

Fig. 5 Influence of additives on shrinkage limit of treated soil (Onyelowe et al. 2021c)

properties showed that the soil belonged to A-7–6 AASHTO group classification and has poorly graded spread according to USCS with high clay content. As reported by Onyelowe et al. (2021c), the added composites of the RHA (RHA, 5%-, 10%-, and 15%-QARHA) behaved almost in a similar way of increased (improved) shrinkage limit of the treated soil as presented in Fig. 5. It can also be noted that 15%-QARHA had greater influence on the shrinkage limits than the other RHA composites (Onyelowe et al. 2021c). This behavior can be attributed to the improved aluminosilicate compounds (Al_2O_3 plus SiO_2 plus Fe_2O_3) contained in Table 4 (ED-XRF chemical compounds) responsible for pozzolanic reaction, hydration, and cation exchange reactions between clayey soil minerals and those from the alkali-activated additive. This agrees with the requirements of ASTM C618 (2019).

4.2 Prediction of Shrinkage Limit (W_S)

4.2.1 Model (1)—Using GP Technique

The developed GP model started with the one level of complexity and settled at three levels of complexity. The population size, survivor size, and number of generations were 100,000, 30,000, and 100 respectively. Equation 1 presents the output formulas for (W_S), while Fig. 7 a shows its fitness. The average error % of total set for W_S is 1.6%, while the R^2 value is 0.968, which agrees with Onyelowe et al. (2021a) and Onyelowe et al. (2021b) in terms of the accuracy of the model technique. The performance accuracy of the GP-based intelligent model to predict shrinkage limit of the expansive soil treated with activated rice husk is over 96%. This shows that the performance of the subgrade can be monitored with high accuracy over its lifetime by using GP-based predictive models (Table 5).

$$W\mathrm{s} = 18 + \frac{\mathrm{P}}{3} - 1.3\ \mathrm{Ln}(W_\mathrm{L}) \tag{1}$$

Table 4 Chemical oxides composition of the additive materials

Materials	Oxides composition (content by weight, %)												
	SiO_2	Al_2O_3	CaO	Fe_2O_3	MgO	K_2O	Na_2O	TiO_2	LOI	P_2O_5	SO_3	IR	Free CaO
Clay soil	12.45	18.09	2.30	10.66	4.89	12.10	34.33	0.07	–	5.11	–	–	–
Rice husk ash	56.48	22.72	5.56	3.77	4.65	2.76	0.01	3.17	0.88	–0.10	–	–	–
activated-RHA	57.37	24.05	7.34	6.44	3.95	0.45	0.20	0.10	–				–

IR insoluble residue, *LOI* loss on ignition

Table 5 Performance accuracies of the developed models

Technique	Developed Eq	Error %	R^2
GP	Equation (1)	1.6	0.968
ANN	Equation (2)	2.0	0.942
EPR	Equation (3)	1.4	0.974

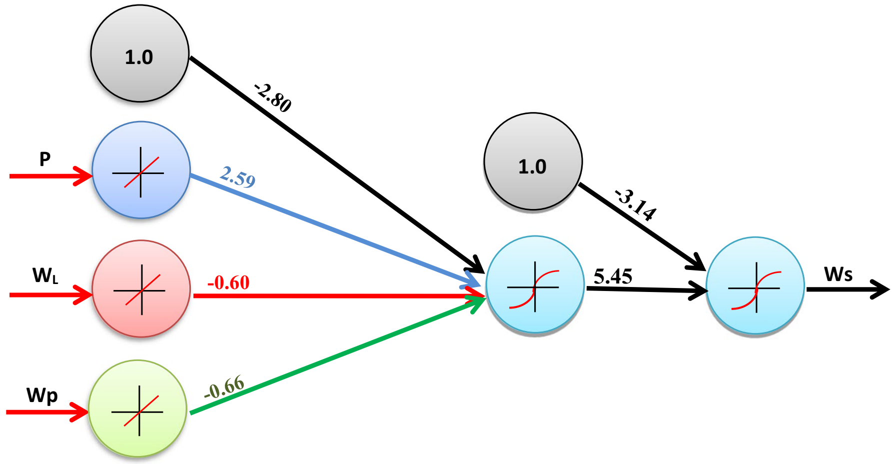

Fig. 6 Layout for the developed ANN and its connection weights

4.2.2 Model (2)—Using ANN Technique

A back propagation ANN with one hidden layer and (Sigmoid) activation function was used to predict the same shrinkage limit (W_S) values. The used network layout and its connation weights are illustrated in Fig. 6. Since the used ANN has a nonlinear activation function, the equivalent equation is very complicated and presented by Eq. (2) with adjoining supplementary equations (Eqs. 3–5) for the substitute parameters of the composite global equation. The average error % of total dataset for this network is 2.0% and the R^2 value is 0.942, which agrees with Chen (1988), Onyelowe et al. (2021a), and Onyelowe et al. (2021b) in terms of the accuracy of the model technique. This shows that the ANN model can predict the shrinkage limit condition of treated expansive soil with over 94% accuracy. The relation between calculated and predicted values is shown in Fig. 7b.

$$\mathrm{Er} = 12.1 + \frac{4.7}{1 + e^{-Y1}} \tag{2}$$

$$Y1 = \frac{5.455}{1 + e^{-X1}} - 3.144 \tag{3}$$

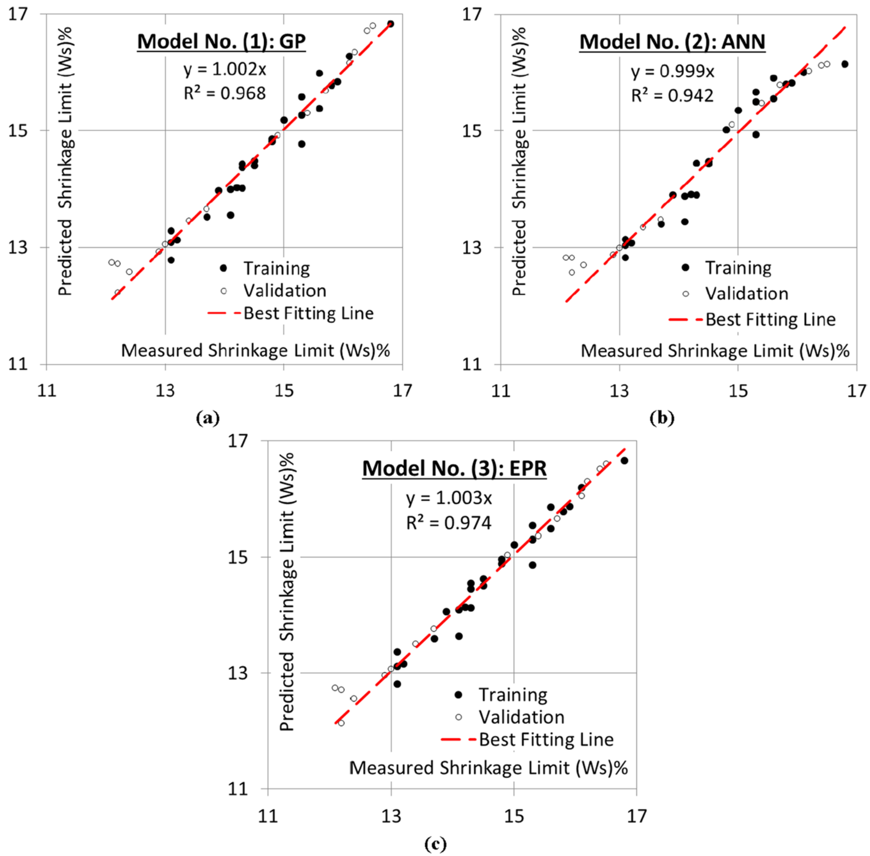

Fig. 7 a–c Relation between predicted and calculated (W_S) values using the developed models

$$X1 = -2.8 + 2.58P' - 0.595W_L' - 0.656Wp' \tag{4}$$

$$P' = \frac{P}{10}; W_L' = \frac{W_L - 32}{53}; Wp' = \frac{W_p - 17}{30} \tag{5}$$

4.2.3 Model (3)—Using EPR technique

Finally, the developed EPR model was limited to quadratic level; for 3 inputs, there are 13 possible terms ($\sum_{i=1}^{i=3} X_i + \sum_{i=1}^{i=3} \sum_{j=1}^{j=3} X_i.X_j + C$). GA technique was applied on these 13 terms to select the most effective 4 terms to predict the values of the shrinkage limit (W_S). The output is illustrated in Eq. 6 and its fitness is shown in Fig. 7c. The average error% and R^2 values were improved to 1.4%–0.974 for the total datasets, respectively, which agrees with Chen (1988) and Onyelowe et al. (2021a) in terms of the accuracy of the model technique. This further shows that EPR-based intelligent model can predict, with high degree of robustness, the shrinkage limit of treated expansive soils with an efficiency of over 97% and an error of 1.4%. This shows also that flexible pavement subgrades can be designed, and constructed with expansive soils treated with activated rice husk ash and its performance forecasted over its lifetime using EPR-based intelligent models, which has been proposed in this work with high and reliable accuracy.

$$W\mathrm{s} = 19.1 - \frac{\mathrm{W_L}}{6.67} + \mathrm{P}.\frac{\mathrm{W_L}}{208} + \frac{\mathrm{W_L}^2}{1250} \tag{6}$$

5 Conclusions

This research presents three models using three (AI) techniques (GP, ANN, and EPR) to predict the shrinkage limit (W_S) values using the measured treatment dosage (P), plastic limit (W_p), and liquid limit (W_L). The results of comparing the accuracies of the developed models could be concluded in the following points:

- The prediction accuracies of ANN and GP models are so close (98.0% and 98.6%) which gives an advantage to the GP model because its output is a simple equation and could be applied either manually or implemented in software unlike the complicated output of the ANN which cannot be applied manually. On the other hand, the prediction accuracy of the EPR model is better than both of them (98.6%), besides that its output is a closed form equation that makes it the optimum model.
- The outputs of both GP and EPR models indicated that W_S values were mainly governed by P and W_L, while W_P has no impact on W_S values.

- Shrinkage limit value (W_S) increases with increasing P value and with decreasing W_L value.
- GA technique successfully reduced the 13 terms of conventional PLR quadratic formula to only 4 terms without significant impact on its accuracy.
- Like any other regression technique, the generated formulas are valid within the considered range of parameter values, beyond this range; the prediction accuracy should be verified.

Abbreviations P: Treatment dosage; W_S: Shrinkage limit; I_P: Plasticity index; W_P: Plastic limit; W_L: Liquid limit; I_S: Shrinkage index; GA: Genetic algorithm; GP: Genetic programming; ANN: Artificial neural network; EPR: Evolutionary polynomial regression; SSC: Swell-shrink cycle; PLR: Polynomial linear regression; SSE: Sum of squared errors; R^2: Coefficient of determination; SSE, R^2: Model performance indices; V: Volume of compacted soil; V_o: Volume of compacted dried soil; M_o: Mass of dry soil; RHA: Rice husk ash; QARHA: Quicklime activated rice husk ash

Supplementary Information The online version contains supplementary material available at https://doi.org/10.1007/s40515-021-00199-y.

Acknowledgements The authors acknowledge the help offered by the laboratory technicians and also to coauthors of this paper for the personal financial contributions toward the lab work.

Author Contribution K. C. O. conceived and oversaw the experimental work, analyzed the results, and prepared the manuscript. A. E. B. prepared the models. L. I. N. prepared the background. I. I. O. prepared the background.

Data Availability The data supporting the results of this research has been reported in the manuscript.

Declarations

Ethics approval and consent to participate This paper conforms to the ethical conditions of this journal and the authors give consent for the publication of this article in your journal.

Consent for publication The authors give their consent for the publication of this paper.

Competing interests The authors declare no competing interests.

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