Modelling soil behaviour in uniaxial strain conditions by neural networks

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Abstract— *It is the primary goal of this research to investigate how neural networks may be used to describe soil behavior under situations of uniaxial strains. Geotechnical engineering issues have been effectively modelled using artificial neural networks (ANNs) during the last several years, particularly soil behavior under uniaxial strain situations. The purpose of artificial neural networks (ANNs), a subset of artificial intelligence, is to simulate, as closely as possible, the human brain and nervous system. Most geotechnical engineering issues may be modelled using ANNs, which have a high degree of complexity [1]. Depending on the size of the research area, it may be necessary to drill numerous boreholes and conduct a number of experiments to determine the structure of the soil layers. It is possible to better comprehend the near-surface geology by learning more about the qualities of the soil layers between boreholes. ANNs training from the samples supplied to them in order to exploit the subtle appropriate data linkages, even if the fundamental links are unclear or the physical interpretation is hard to describe [1]. ANN is able to categorize the various layers at varying depths, and in order to ascertain the thickness of each layer at a specified level, multi-layer neural networks are trained independently. Data from the test boreholes was fed into the neural network, and the results were compared to real site investigation data to see how well the neural network performed in predicting changes in soil behavior. The results will indicate that ANN models are quite good at making predictions.*

Keywords: Artificial neural networks (ANNs, Data, C.Testing, Training, MSE, MAE, and RMSE.Validation.

I. INTRODUCTION

Soil stiffness under uniaxial strain situations may be accurately predicted using an artificial neural network, as this research shows the relationship between fundamental soil parameters and strain soil behavior. One of the most significant tasks in ground improvement is to determine the coefficient of lateral earth pressure at rest which is used to build and analyze earth-retaining systems, lateral loads, and piles and pier foundations. It requires very technical testing processes [1,2]. Monitoring the soil's quality by looking at its physical characteristics is an essential component in the process of determining whether or not a geotechnical engineering is environmentally friendly. Soil quality may be monitored and assessed based on the physical characteristics of the soil, such as its resistance to soil penetration. Soil variables such as bulk density and water content may influence penetration resistance, which can be predicted using an artificial neural network (ANN). ANNs have been used to handle a variety of agricultural issues. The goal of this study is to use statistical analyses, especially regression analysis and ANN modeling, to examine the behavior of soil penetration resistance as evaluated by the cone index at various bulk density and water content levels [2,3].

The distinct soil layers at various depths may be classified using a multi-layer neural network that has been trained. It's worth noting that the ANN model can calculate the depth to which each layer is, after it's been trained. Test drilling data was fed into the network and then compared with findings from real site investigations to confirm that neural networks performed as expected when it came to predicting soil layer changes. The trained ANN model's accuracy in prediction is about 90% [3].

For each geotechnical project, the retrieved data might be utilized for the first site investigation. When training ANNs, it is important to choose input instances that are similar to those that have already been taught [4]. In other words, an ANN model presented may interpolate input-output pairings; future study will define the correctness of ANN models in data extrapolation. An accurate prediction of underlying soil layers in a study area may be made using an artificial neural network (ANN) model that was developed. It is the primary goal of this research to examine how neural networks may simulate soil behavior under situations of uniaxial strain.

II. RESEARCH PROBLEM

The main problem that will be solved by this paper is to discuss how neural networks may be used to simulate soil behavior under situations of uniaxial strain. Under high geostrain settings, sudden release of strain energy from rocks holding strain energy is a determining factor in causing catastrophic consequences in the deformation and collapse of rocks. The development of elastic strain energy and dissipated energy in the rock may be anticipated using the strength, deformation, and AE properties of the rock [6]. In addition, the AE characteristic signals were examined in relation to the confining pressure and dip angle. Final analysis is done using neural networks to examine how fractured rocks in pre-peak stages of uniaxial strain circumstances accumulate and evolve input and elastic strain energy as well as dissipated energy.

III. LITERATURE REVIEW

A. Artificial neural networks (ANNs)

Automated neural networks are an area of artificial intelligence (AI) because they allow us to model relationships and interdependencies between various system input variables, and they may then use this information to make predictions about the future [7,8]. If there is a pattern in the data, it can be found using any collection of numbers. Numerous uses of this technique in the geotechnical engineering have been documented during the last two decades. Here, we focus on establishing nonlinear stress-strain correlations for geotechnical properties. In recent years, computerized technologies that resemble organic nerve systems have become popular. More and more engineers are turning to "artificial neural networks" for their problem-solving and data analysis needs. They have been used in civil engineering since the late 1980s[8]. Process optimization, the computed value corresponding to the vehicle axis load, performance and manufacturing process modeling, seismic risk prediction and cost estimation are just a few of the many applications now available. For a variety of reasons, neural networks have become increasingly popular, the most important of which are their ability to use information processing properties in the brain that are beyond the reach of conventional programming techniques, such as learning and generalization, the ability to propose solutions for issues where the input may have some errors, and calculating related time responses for issues that have changing conditions.

In the field of complex systems research, ANN has been used fruitfully to the tasks of finding patterns and modeling real-world issues related to complicated behaviors including nonlinear functional interactions. The potential of ANN to uncover the mapping across many data domains is something that has piqued the attention of a significant number of academics in the field of geotechnical engineering [9]. A variety of factors are used to categorize ANNs, including the learning condition, model topology (feedforward vs. recurring networks), the number of features, and the training technique [9]). An attempt is made here to clear up some of the complexity and misunderstandings surrounding back propagation ANN models, and to advocate their usage in soil stabilization issues for more accurate solutions.

B. Predicting soil behavior with the help of an ANN

It is impossible to anticipate the behavior of soils even in their natural condition because of the extreme variety they exhibit due to the unpredictable and inaccurate chemical and mechanical processes involved in their production. Post-stabilization behavior of treated clays has been modelled using a variety of mathematical and graphical models for the goal of designing and constructing structures. For these procedures, in-situ post-stabilization behavior must be anticipated based on laboratory findings from a small number of samples. There are several factors that may affect a soil's post-stabilization behavior, including the kind of soil, the amount of binder, the temperature at which the soil is cured, the moisture content of the soil, the compaction technique and effort required, the soil's flexibility, and more [10]. It is considerably more difficult to forecast the soil's behavior because of the wide range of input factors, the numerous laboratory tests necessary, and the unknown link between the variables placed together [10]. Many research focuses on a small number of factors and use basic mathematical frameworks to select relevant subdomains to the variables in simplifying the problem.

The implementation of ANN has shown successful outcomes in terms of the precise estimate of mechanical properties of stabilized soils for a variety of applications. For in-situ prediction of treated clay soil behavior after stabilization, ANN is a better tool because it is capable of learning the relationships between more experimental variables and mapping those variables to the desired output domain using weights that have been appropriately calibrated. An additional benefit of ANNs over conventional regression analysis is their flexibility in discovering relationships for highly non-linear data, which is common in civil engineering applications [11,12]. ANNs may concurrently manage many variables of the study utilizing the same experimental dataset. In the next sections, an overview of research modeling different soil parameters is offered. The purpose of this review is to investigate the study's input parameters, the quantity of data used in model construction, the training method used, the model's hyperparameters, the model's performance, and, lastly, the findings or predictive models created.

C. Testing, Training, and Validation

Most neural networks that are used to simulate geomechanical parameters of stabilized soils are trained under supervised settings as previously described. Rather than using the whole collection of input data to train the model, just a subset (the training dataset) is used to establish relationships between the variables. Rather of recognizing this input, the network feeds it back over and over again in order to learn from it[12]. If the network learns in a stepwise fashion, it will eventually converge to a lower error range as it goes through each iteration. The degree to which the model converges is affected by the reliability of the dataset used for training [12]. It is possible that a dataset does not include enough independent variables to allow a model to explain the data, resulting in non-convergence. If the sample size is too little, the network may end up remembering instead of learning. Because of this, a subset of the data must be set aside for the sake of assessing the training. This is the data used for verification. Therefore, it would be necessary to constantly monitor and adjust the number of neurons in each hidden layer, as well as any hidden layers' number and activation function, in order to create an appropriate model. The trained model is tested repeatedly on the validation dataset as part of the model validation process [13]. Unbiased assessment of the model's understanding of training data. Evaluate datasets, which were never viewed by the model before now, are used to test its ability to predict outcomes. Cross-validation involves dividing the data into two halves and then comparing the results. In a cross-pattern, the dataset is used for training and validation.

D. Modeling the behavior of soil under uniaxial tension

An example of uniaxial strain is when the 11 (axial) strain is nonzero, but all other strains are zero[14]. To understand the functional relationships and inter-variable dependencies in a huge collection of data including several variables, it is very tiresome to utilize a more complex instrument or approach, such as the notion of artificial intelligence. Soil stabilization using ANN is a relatively recent technique, according to Reference [68]. However, this work reveals that it is becoming a more dependable tool in the construction of geotechnical property prediction models for stabilized clays. The capacity of artificial neural networks (ANNs) to learn the functional linkages and inter-variable dependencies that exist within vast collections of predictor factors provides them a significant advantage over more conventional methods of regression analysis, which involve laborious mathematical techniques [14]. Regression analysis will take longer to run on certain research because of the extensive database of soil attributes they've used. If a variable in the dataset is changed, the analysis must be redone, making the old methods even more time consuming. Such variations may be readily addressed by utilizing an ANN, and this offers the ANN the benefit of a tighter fit to the experimental data for your parameter of interest since a bigger dataset contains a broader range of soil reactions. The ability to model several dependant or target variables concurrently is another feature of ANN[14,15]. A dataset and one or more dependent variables may be linked using ANN, which can then assign the coefficients needed to achieve different goals. When many dependent variables are simulated concurrently, some research have been able to produce accurate prediction models for the dependent variables[15]. This is another another time-saving benefit. It is clear from that the model's performance is not directly related to the hidden layer's number of neurons. Model training requires a significant number of neurons for optimal performance, although the exact number depends on the difficulty of the issue being studied. The use of ANN in evaluating treated clays' performance and post stabilization behavior has been shown to be very reliable. A statistical evaluations of ANN's performance reveal that they outperform traditional regression models in several cases. A major benefit of ANN regression analysis is in the fact that it has a high R2 and low MSE, MAE, and RMSE. ANN models with just one hidden layer were found to be the most common, according to the research.

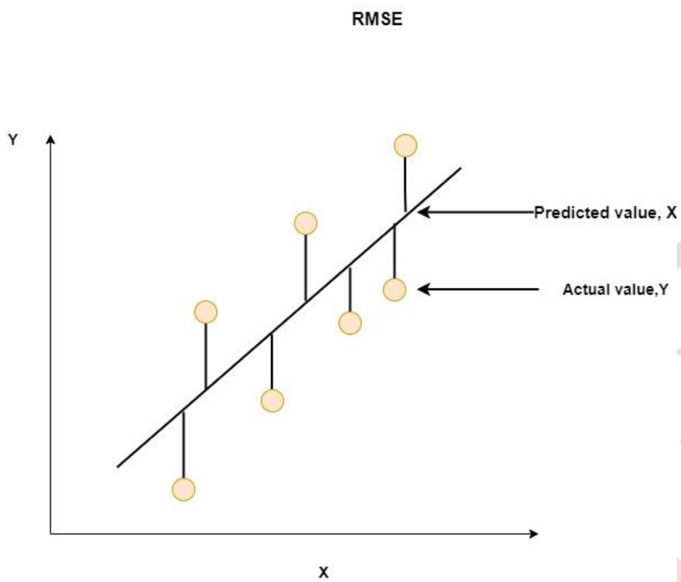

Fig i: An illustration of RMSE regression analysis

Using two hidden layers for analysis was only employed in two research [16]. Regression analysis in soil stabilization issues may be simplified utilizing a single hidden layer, according to other research. The model's robustness and generalizability are both enhanced by the high quality and large quantity of the training set. Many data collection in the research a tiny dataset for analysis, raising doubts about the models' reliability in real-world situations [16].

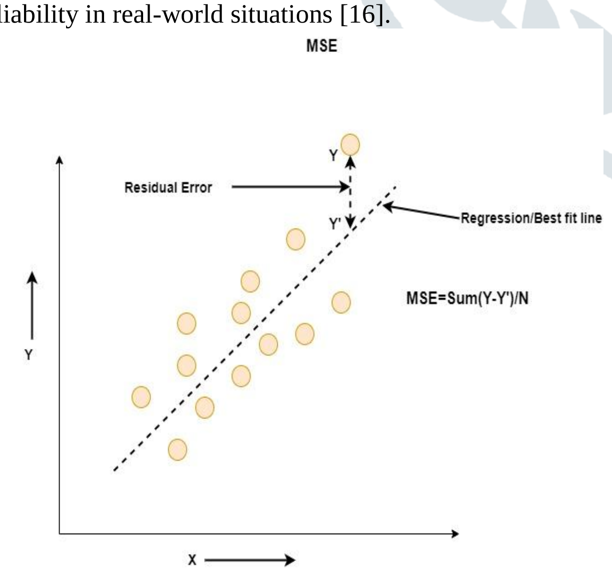

Fig ii: An illustration of MSE regression analysis

IV. SIGNIFICANCE TO THE U.S

The use of artificial neural network (ANN) models of soils is essential for accurately predicting the behavior of geotechnical constructions in the United States. Over the past three decades, a vast variety of methods based on diverse constitutive principles have been presented. All of them make the same assumption, which is that there is a mathematical framework behind the model, and that the material parameters that match to the framework that is assumed must be determined via the use of physical material testing [16,17]. There are a lot of material parameters in complicated constitutive theories, and a lot of them have no physical significance, they are tough to identify, and you have to figure out what they are by trying different things out using numerical simulations. Numerous characteristics of soil behavior, such as its stiffness at small stresses, its increased stiffness on reversal of strain route, and its impact on rotation of primary strain axes, are crucial in geotechnical projects.

V. FUTURE IN THE U.S.

For geoscientists, predicting earthquakes in the United States is an excellent way to learn about various ML techniques and to teach ML in geosciences programs, since it serves as an excellent introduction challenge. A number of students and academics have utilized the top five ways to evaluate and contrast the intricacies of rival machine learning methods, as well as to adapt and enhance the approaches for usage in different fields. High-performance computing systems are also needed to try out novel ideas and apply them to new sectors. The liquefaction machine learning model is still being improved by the researchers. According to the researchers, further study is required to build machine learning models that can be applied to various earthquakes and geologic situations [18]. As part of their work, earthquake investigators will concentrate on identifying the processes that lead to structural failure or collapse, as well as planning and mitigating earthquake risk by implementing the best repair plans, performance-based improvements, and specialized solutions possible. We provide property owners, the legal and insurance communities, as well as governmental organizations, with multifaceted, all-encompassing help both during and after earthquakes.

VI. CONCLUSION

This research examined how neural networks may be used to simulate soil behavior under uniaxial strain settings. The study demonstrates how an artificial neural network is reliable and can be used to simulate different aspects of soil behavior enabling straightforward prediction of soil reaction without the need for complex experimental methods. Regression models with excellent correlation should be constructed using an artificial neural network with a large dataset. Although the models have performed well, several investigations in stabilised clay regression analysis have employed tiny data sets. The generalizability of the models may be increased by training them on a bigger dataset that contains a wider range of probable soil behavior. The most often utilized ANN design for predicting soil geotechnical properties and modelling the response to uniaxial strain situations is a shallow network with a single hidden layer.

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