Modelling Soil Behaviour in Uniaxial Strain Conditions By Neural Networks

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***Abstract*— *The main aim of this research is to examine how neural networks can describe soil behavior under situations of uniaxial tension. Geotechnical engineering issues have been effectively modelled using artificial neural networks (ANNs) over the past several years. Artificial neural networks (ANNs) are a kind of artificial intelligence (AI) that aim to replicate the brain and nervous system of humans [1]. Most geotechnical engineering issues may be effectively modelled with ANNs. The goal of this work was to use ANNs to figure out how much dirt is buried under the surface. Depending on the size of the research area, it may be necessary to conduct a number of experiments and drill a number of boreholes in order to evaluate the soil layer structure [1]. The near-surface geology may be better understood by learning more about the qualities of the soil layers between boreholes. A neural network (ANN) learns from instances of data in order to grasp the nuances of functional data correlations even when the underpinnings of such interactions are obscure or difficult to understand on the physical level.*

Keywords: Genetic Programming, soil-structure interaction, Artificial intelligence, Artificial Neural Network (ANN)

I. INTRODUCTION

The ability to accurately forecast the behavior of geotechnical constructions relies on the use of appropriate soil models. In the past three decades [1], a vast variety of models based on diverse constitutive theories have been presented. All of them presuppose an a priori mathematical model framework and need physical material testing to identify the material properties that match to the expected framework. A great deal of the information in complicated constitutive theories is based on numerical simulations, which can only be determined through trial and error. As a result, it is difficult to represent all aspects of soil behavior, including stiffness at small stresses, increased stiffness on reversing stress paths, and the impact on stress axes' rotations. Despite decades of study into soil's mechanical characteristics, very little is understood about how soil behaves. Simplified hypotheses are used to address multivariable geotechnical issues using conventional approaches such as mathematical and experimental methods. A closer look at these techniques reveals that they are unable to capture the intricate behavior of soil [2]. It is vital to use a replacement approach in which effective parameters are considered concurrently, as well as the capacity to generalize and learn directly from experimental Fidata (by considering errors). Many geotechnical engineering challenges have been successfully solved using neural networks in recent years. As a result of the usefulness of neural networks in resolving complicated issues, neural network research has continued. Various boreholes must be bored and many tests conducted in order to determine the structure of the soil. This procedure is very costly and time-consuming [3].

As the accuracy of interpolating soil layer structures and qualities in between boreholes (i.e. distances between boreholes) increases, so does the cost of geotechnical assessments, making it easier to plan out building projects properly [4]. Human brain characteristics such as learning, data generalization, managing missing data and parallel computation were not accessible in earlier systems [5]. ANN (as an intelligent system) exploits these skills. Geotechnical engineering is a popular application of artificial neural networks (ANNs), and many academics have looked at it. On the basis of cone penetration test results, an artificial neural network model can accurately anticipate complicated soil. In this article, neural networks are used to describe soil behavior under circumstances of uniaxial strain.

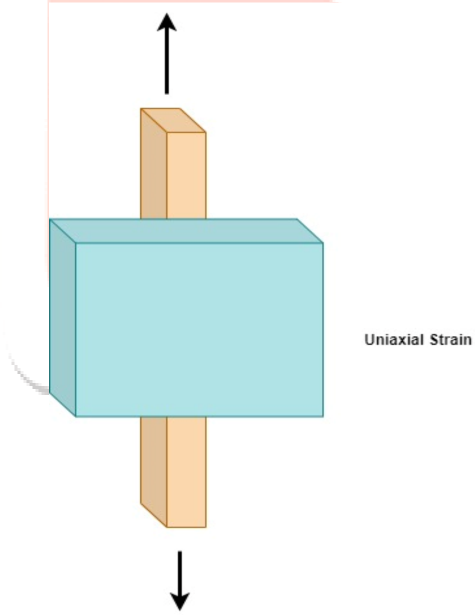

Fig i: An example of a uniaxial strain

II. RESEARCH PROBLEM

The main problem that will be solved by this paper is to analyze how neural networks can be used to model soil behaviour in uniaxial strain conditions. Complex nonlinear interactions between input and output data sets may be identified by using ANNs, which are adaptable mathematical frameworks. It is possible to generalize ANN models [6]. The non-linear and complex interactions among variables in a system may be captured using ANN models, which can deal with poor or partial data. The ANN model has a lot of promise in geotechnical engineering because of its unique learning, training, and prediction capabilities. Many geotechnical engineering challenges have recently been solved using artificial neural networks (ANNs).

III. LITERATURE REVIEW

A. Artificial neural networks

Computerized technologies that resemble organic nerve systems have become more popular in recent years. "Artificial neural networks" are tools found in almost every discipline of engineering research, and their application is steadily rising. Since the late 1980s, they have been used in civil engineering [7]. 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. One of the most important reasons neural networks are becoming more popular is that they can take full advantage of brain-based information processing properties not accessible through conventional programming techniques, such as learning and generalizing abilities, the ability to suggest solutions to problems where the input contains errors, and finally, the ability to calculate related time responses for problems that have complex causes.

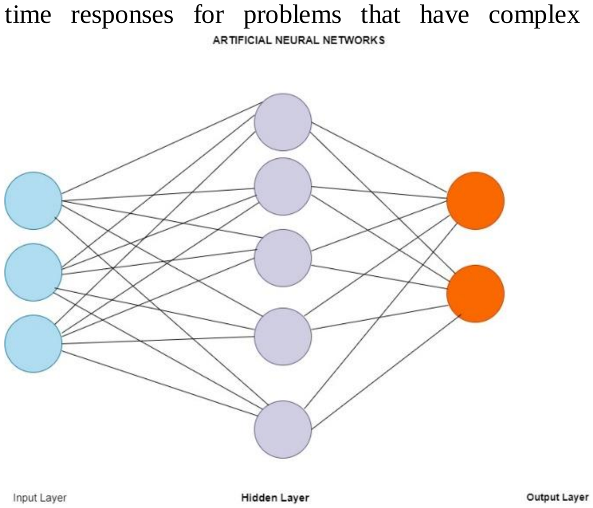

Fig i: An illustration of Artificial Neural Network

Adjusting weights between nodes in a neural network is done to correct for differences between actual output values and the desired output values. Numerous rules for learning have been devised. The most often used learning rule is back propagation [9,10]. Pattern and function approximation are two areas in which the back-propagation learning rule is most often used. A network's mean-squared error may be reduced by adjusting the weights and biases of the network. In order to do this, the weights and biases in the network must be adjusted in the direction of the steepest error drop. Back-propagation across each hidden layer is used to produce error vector derivatives for the network's output layer [11]. The term "training" refers to the process of continually feeding the network input vectors, calculating the errors based on the goal vectors, and then using the learning procedure to identify new weights and biases. After a certain number of epochs or a minimum mean-squared error has been reached, the cycle is repeated. A neural network model that can predict a target value for a given input value is presented at the conclusion of this training phase.

B. Modeling input and output parameters using neuronal networks

Based on the MATLAB toolbox, an ANN program is employed in this study (MATLAB). To train the ANN, the authors required a collection of input and output pairings that were already known to them. There are normally two sets of input-output pairs available for use. The weights of the connections in the networks are determined using the learning or training set. After training, the neural network's performance is assessed using the testing set [12]. Because of the limited amount of data, it was decided to rely on information from the soil layers for the categorization process. Input parameters included the x, y, and z coordinates and depth. The output of the ANN model was a related category based on the input parameters, which will be explained in the next paragraph. The grain size of soil samples determines the type of soil in the Unified Soil Classification System (USCS). A total of eleven soil categories were identified in the research region. Symbols might be assigned to certain groups in this manner. It was found that in this study, 75 percent of the data was utilized in training and 25 percent in testing [13].

Algorithms with a single hidden layer are used to get the RMSE values. Networks that have consistent features were used to establish the optimal number of neurons in the hidden layer; subsequently, a variety of parameters were changed and various values were assigned to neurons so that the findings were compared to find the optimal number of neurons. In order to arrive at an accurate estimate of the number of neurons, we used the RMSE method, which has already been explained. Two, three, four, five, six, seven, eight, nine, and ten neurons are learned in hidden layers of back-propagation neural networks. Different neurons' RMSE readings are displayed. Seven neurons in a network with a momentum of 0.2, a learning rate of 0.33, and an epoch of 500[12] had the lowest RMSE [13]. A model with a reduced root-mean-square error (RMSE) was chosen for the aforementioned situation.

C. Models of Constitutive Behaviour Based on Artificial Neural Networks (ANN)

When a collection of "causes" and "effects" are identified, ANNs may be used to identify the link between them. It's possible to find a pattern in just about any collection of numerical data [12]. In the last two decades, this technique has been used by a slew of scientists throughout the physical and biological sciences. There is a lot of emphasis here on generating nonlinear stress-strain relations for geomaterials. With the right data, artificial neural networks (ANNs) may be utilized to model the stress-strain response of any material. When it comes to strain rate components, the resultant stress rates serve as both the source and the impact. The tangential stress integration matrix does not need to be updated or reconstituted in order for a NNCM to accurately describe stress-strain behavior. In [13], you'll find all the information. For the sake of completeness and coherence, a succinct explanation is provided below. From the associated incremental strain vector, an incremental stress (as opposed to total) vector may be derived.

D. Hardening Soil Model (HSM)

It is a nonlinear elastic-plastic model with a Mohr Coulomb failure criterion, as detailed in PLAXISTM Manual's Hardening Soil Model. An improved version of Duncan & Chang's nonlinear elastic hyperbolic model is presented in [13], where deviatoric hardening is applied to the Mohr Coulomb yield surface. Non-associated flow rules are established, which are determined by a dilatancy angle lower than the peak frictional angle. It may be applied to lose to medium-density sands and soils that are ordinarily cemented to mildly over-consolidated. Nonlinearity before failure is a shortcoming of linear elastic-plastic models, which this approach addresses. Cap on deviatoric stress – mean effective stress space is also included in the package. For the sake of comparison, we've used the normal medium dense parameters [13] as a starting point. The PLAXISTM software instructions should be consulted for a complete list of parameters, even though some of them are recognizable to engineers. Stress and strain responses of the sand under different experimental settings, such as Triaxial

Loading In Compression (LC) and Extension (LE) [13], are derived from the data in Table 1 [14,15]. These results were obtained by the use of stress drains that have been carefully monitored and managed. The PLAXISTM program with HSM model was used to analyze a single finite element exposed to uniform stress conditions [13]. q and p' are the deviatoric and effective mean stress routes in space, respectively. Three distinct confining pressures of 50 kPa, 100 kPa and 150 kPa are employed for each of the aforementioned stress paths [14]. These simulations yielded stress-strain data that was utilized to train the NNCM.

IV. SIGNIFICANCE TO THE U.S

When it comes to engineering and construction projects in the United States, finite element analysis (FEA) is one of the most important building components. In Geotechnical Engineering, one of the most important goals of study has been to develop realistic stress-strain behavior models. Using Neural Networks, a more data-driven method may be devised to account for this problem. Soil behavior may be modelled using neural networks. The modeling of soil stress-strain behavior focuses mostly on the Neural Network approaches that might be beneficial in construction [14,15]. The stress-strain connection is precisely predicted by the Neural Network. Even "noisy" datasets may be utilized to forecast the stress route. If you train neural networks on a training dataset including noise, however, they can recognize patterns in that noise. Ultimately, this is an endeavor to construct a neural network modeling approach with the goal of creating data-driven modeling techniques. ' It is critical for project owners, contractors, and designers to be able to determine the most important criteria for a successful project performance. A well-executed construction project may benefit from an understanding of these critical elements.

V. FUTURE IN THE U.S.

According to a recent report, data collection efficiency and standardization may become more of a focus in U.S. neural model research in the next years. It is becoming clear that artificial neural networks (ANNs) may be used to build structures. When it comes to the design of a dry precast concrete connection, ANNs are often used. An automated data gathering system should be implemented to guarantee long-term data quality and sustainable data updates. As a result, in many geotechnical and civil engineering businesses, it would serve as an effective management platform for US building projects. For a considerable amount of time, the branch of study that has shown the greatest promise has been neural network modeling. They've just stepped up their pace. It was only possible to use one hidden layer in the early days of neural networks yet the results were still far better [18]. Because of their established effectiveness in handling complicated geotechnical issues, neural networks approaches are becoming more essential. Small and medium-sized businesses (SMEs) as well as individuals are increasingly able to take use of open-source software and high-performance computer capabilities.

VI. CONCLUSION

This research offers recommendations for neural network modeling of soil behaviour under uniaxial strain situations. Using an artificial neural network, this research accurately predicts soil stiffness under circumstances of uniaxial strain, confirming the relationship between fundamental soil parameters and stress-strain soil behaviour. The comparison of neural network predictions with empirical equations demonstrates that the neural network provides a more accurate and broad solution to the issue. A effective forecast of engineering structures' behaviour can only be made with the use of accurate material models, according to the research. In the past three decades, a vast variety of models for geomaterials based on diverse constitutive theories have been published, showing a substantial variance in their characteristics. Mathematical frameworks and material characteristics must be determined via physical experiments in order to use any of these models. A great deal of the information in complicated constitutive theories is based on numerical simulations, which can only be determined through trial and error. A single model has failed to represent the multiple aspects of soil behaviour, such as stiffness at small stresses and increased stiffness on the reversal stress path, as well as the impact of rotation of the primary stress axes. Models with more complexity are envisaged in the future.

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