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# Application of Artificial Intelligence for the prediction of unconfined compressive strength of soft soil stabilized with copper slag geopolymer

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***Abstract :*** The unconfined compressive strength (UCS) of soft soils is a critical parameter in determining their stability and suitability for construction purposes. In recent years, copper slag-based geopolymers have emerged as a sustainable and effective soil stabilization method, improving the mechanical properties of soft soils. However, the prediction of UCS for such stabilized soils remains complex due to the variability in soil properties, geopolymer mix ratios, and environmental conditions. This research explores the application of Artificial Intelligence (AI) techniques, specifically machine learning models, for predicting the UCS of soft soils stabilized with copper slag geopolymer. By leveraging a comprehensive dataset of experimental results, AI models, including Artificial Neural Networks (ANN), were developed and trained to predict UCS based on input variables such as copper slag content, activator concentration, curing time, and soil properties. The results demonstrate the efficiency and accuracy of AI in predicting UCS, providing a powerful tool for optimizing soil stabilization practices and reducing the need for extensive laboratory testing. This study highlights the potential of AI-driven approaches in geotechnical engineering, contributing to the advancement of sustainable soil stabilization technologies.

***Keywords*** **-Artificial Intelligence, copper slag, soft soil.**

## I. Introduction

Soil stabilization is a critical process in geotechnical engineering, particularly when dealing with soft soils, which exhibit low strength and high compressibility. Traditional stabilization techniques often rely on cement or lime, which, while effective, contribute to environmental concerns such as high carbon emissions[1]. In response to the growing demand for sustainable construction practices, the use of industrial by-products like copper slag has gained attention[2,3]. Copper slag, a waste material from copper smelting, can be transformed into a geopolymer, offering an eco-friendly alternative for soil stabilization.

Geopolymers, which are inorganic polymers formed by the reaction of aluminosilicate materials with alkaline solutions, have shown significant promise in enhancing the strength and durability of soils[4–6]. Specifically, copper slag-based geopolymers have been found to improve the unconfined compressive strength (UCS) of soft soils[7], making them more suitable for construction projects. However, predicting the UCS of stabilized soils is challenging due to the variability in material properties and mix proportions.

Artificial Intelligence (AI) offers a novel solution to this challenge by utilizing data-driven approaches to model complex systems. Machine learning techniques, in particular, can efficiently analyze large datasets and identify patterns that may be difficult to discern using traditional methods[8–11]. This study focuses on applying AI, such as Artificial Neural Networks (ANN) to predict the UCS of soft soils stabilized with copper slag-based geopolymers. By developing accurate prediction models, this research aims to optimize the stabilization process, reducing the need for extensive laboratory testing and contributing to more sustainable geotechnical practices.

## II. Methods and materials

Soil

The primary materials used in this study include soft soil, copper slag, and alkaline activators. The soft soil was sourced from a local site in Raipur, characterized by high plasticity and low natural strength, making it an ideal candidate for stabilization. Copper slag, a by-product of the copper smelting process, was collected and processed for use as the primary stabilizing agent. The chemical composition of the slag, rich in silica and alumina, makes it suitable for geopolymer formation. Alkaline activators, typically a combination of sodium hydroxide (NaOH) and sodium silicate ($Na_2SiO_3$), were used to initiate the geopolymerization process.

Copper Slag:

Copper slag in this study is collected from Gujarat is a by-product of copper smelting industries, primarily in areas like Dahej. It contains silica, iron oxides, and other trace metals, making it a valuable material for industrial use. Gujarat's copper slag is often utilized in construction for soil stabilization, concrete production, and as a substitute for sand in road construction. Due to its high strength and durability, it enhances the mechanical properties of the materials in which it is used, while also contributing to environmental sustainability by recycling industrial waste.

Sample Preparation:

The copper slag-based geopolymer was prepared by mixing copper slag with the alkaline activators in varying proportions. The sodium hydroxide solution was prepared at different molar concentrations (e.g., 8M, 10M, 12M) to study its effect on strength development. The slag and activators were thoroughly mixed, and the resulting mixture was then added to the soft soil at different percentages by weight (e.g., 10% to 40% copper slag). The mixtures were homogenized and compacted into molds to form cylindrical samples for unconfined compressive strength (UCS) testing.

Curing:

The prepared samples were cured under controlled conditions for varying durations (7, 14, and 28 days) to assess the effect of curing time on the strength gain. Curing was conducted in a temperature-controlled environment to ensure uniformity across all samples.

## III. RESULTS AND DISCUSSION

### 3.1 UCS Testing:

After curing, the samples underwent UCS testing as per ASTM standards. The compressive strength was measured to evaluate the effectiveness of copper slag-based geopolymers in improving soil strength.

### 3.2 Artificial Intelligence Modeling

An Artificial Neural Network (ANN) is a computational system modeled after the human brain's neural structure. It is composed of layers of nodes, or neurons, that process information. ANNs are used for recognizing patterns, learning from data, and making decisions based on inputs. The network's architecture typically includes an input layer, one or more hidden layers, and an output layer. Neurons in each layer are connected to the next, with weights assigned to each connection to represent its importance. These weights are adjusted during training to minimize errors using algorithms like backpropagation. ANNs are widely used in tasks such as classification, regression, image recognition, and natural language processing, making them essential in fields requiring adaptive learning and complex data analysis.

### 3.3 Design of ANN model

In this study, a feed-forward backpropagation network algorithm using the Levenberg–Marquardt (LM) training function was chosen for the Artificial Neural Network (ANN) model due to its strong training performance. MATLAB was used to develop and analyze the ANN. The model consists of an input layer, one or two hidden layers, and an output layer. The 'tansig' function was applied in the input layer, and the 'purelin' function in the output layer. To prevent overfitting, the "early stopping" method was employed, which increases epochs until the validation set error stops decreasing. Overfitting was avoided by assessing various epoch counts and errors. Underfitting was not an issue given the amount of data and the model's design.

Input parameters included copper slag content (CS%), NaOH concentration (M), curing time (days), and the sodium silicate to sodium hydroxide ratio (SSR). The output layer simulated Unconfined Compressive Strength (UCS) (kPa). Different neuron counts and hidden layers were tested to train the model, adjusting neurons from 10 to 20 in increments of 2. Several ANN models with varying architectures were trained for up to 1000 epochs to meet a performance goal of 1e-07. A total of 232 input data sets were used, with 70% for training, 15% for testing, and 15% for validation.

The effectiveness of the developed ANN models was assessed using the average absolute percentage error (AAPE) and the correlation coefficient (R).

### 3.4 Construction of ANN model

An artificial neural network (ANN) model was developed using different architectures by adjusting neuron counts and hidden layers. Each model was trained, and the coefficient of determination ($R^2$) for testing, training, and validation was calculated, along with the average absolute percentage error (AAPE) to assess validation error (Table 1). While $R^2$ values were similar across models, the 4-12-1 architecture was identified as the best, as it achieved the lowest AAPE value of 0.56, meeting the performance target of 1e-07.

*Table 1 Comparison of different ANN model architectures*

| ANN Model | Layer Architecture | $R^2$ (Training) | $R^2$ (Testing) | $R^2$ (Validation) | $R^2$ (Overall) | AAPE |
|---|---|---|---|---|---|---|
| ANN1 | 4-6-1 | 0.982615 | 0.982851 | 0.980447 | 0.981923 | 0.898553 |
| ANN2 | 4-7-1 | 0.984515 | 0.968467 | 0.979971 | 0.980447 | 0.952665 |
| ANN3 | 4-8-1 | 0.984752 | 0.979947 | 0.94442 | 0.976529 | 3.968908 |
| ANN4 | 4-9-1 | 0.984418 | 0.974831 | 0.972969 | 0.979931 | 2.00494 |
| ANN5 | 4-11-1 | 0.98497 | 0.960437 | 0.977851 | 0.977963 | 0.746229 |
| ANN6 | 4-12-1 | 0.991088 | 0.984004 | 0.987295 | 0.987982 | 0.556793 |
| ANN7 | 4-13-1 | 0.984434 | 0.960084 | 0.962689 | 0.975065 | 3.115969 |
| ANN8 | 4-5-5-1 | 0.975221 | 0.926803 | 0.976709 | 0.967024 | 3.460533 |
| ANN9 | 4-5-9-1 | 0.954714 | 0.951654 | 0.975943 | 0.952644 | 1.735951 |
| ANN10 | 4-7-5-1 | 0.984287 | 0.972025 | 0.982766 | 0.982919 | 1.014082 |
| ANN11 | 4-7-6-1 | 0.970786 | 0.970665 | 0.955701 | 0.968894 | 2.988037 |
| ANN12 | 4-7-8-1 | 0.976366 | 0.968125 | 0.973928 | 0.97157 | 1.19771 |
| ANN13 | 4-8-6-1 | 0.98497 | 0.967675 | 0.977124 | 0.98397 | 0.777337 |
| ANN14 | 4-8-8-1 | 0.98327 | 0.96052 | 0.957981 | 0.975007 | 2.718221 |
| ANN15 | 4-9-5-1 | 0.972313 | 0.962449 | 0.975861 | 0.962713 | 1.879144 |
| ANN16 | 4-9-7-1 | 0.98288 | 0.97202 | 0.976994 | 0.982179 | 1.156826 |
| ANN17 | 4-10-9-1 | 0.946847 | 0.94746 | 0.921159 | 0.939803 | 4.120702 |
| ANN18 | 4-10-24-1 | 0.984946 | 0.94541 | 0.964572 | 0.96768 | 2.397226 |
| ANN19 | 4-20-10-1 | 0.984722 | 0.963319 | 0.892946 | 0.967119 | 11.57151 |
| ANN20 | 4-25-25-1 | 0.947744 | 0.924368 | 0.958289 | 0.94692 | 4.208771 |

**3.5 Validation of the constructed models**

The optimal ANN model (ANN6: 4-12-1) was validated using datasets not involved in its development. The model's accuracy was evaluated by comparing predicted unconfined compressive strength (UCS) with observed UCS from test data. The coefficient of determination assessed the correlation between predicted and actual values. As shown in Figure 1, there is a strong correlation, indicating good predictive performance. Figure 2 presents the coefficients of determination, confirming the ANN model's high statistical reliability and strong agreement between predicted and observed UCS values.

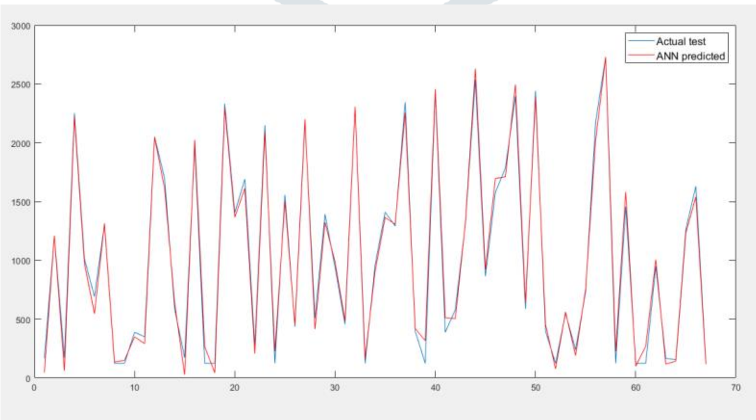


*Figure 1 Actual results vs ANN model predicted UCS values comparison*

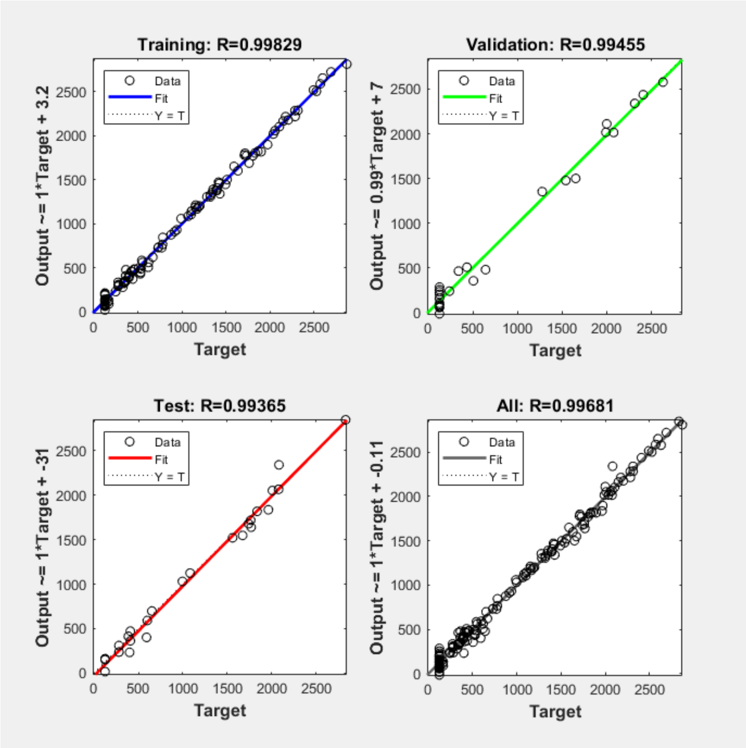


*Figure 2 Coefficient of determination values of ANN model*

### 3.6 Limitations of the constructed models

The ANN model developed shows high predictive accuracy and statistical reliability for estimating UCS, potentially minimizing the need for extensive UCS testing. It focuses on the input-output variable relationship but has limitations in accurately predicting soil compressive strength. The model's accuracy is influenced by factors such as copper slag content (10-40%), NaOH concentration (8M-12M), curing period (0-28 days), and sodium silicate to sodium hydroxide ratio (0.5-1.5). Predictions outside these ranges may be less accurate, and other factors like particle size, temperature, and mixing homogeneity also impact UCS evaluation.

## IV. CONCLUSIONS

The study developed an artificial neural network (ANN) model to predict the strength characteristics of a specific soil type. The model proved to be statistically significant, meaning it provides reliable predictions based on the data it was trained on. Its effectiveness in forecasting soil strength highlights its potential utility in soil engineering applications. However, the model's applicability is confined to particular conditions. It is calibrated for a range of copper slag content between 10% and 40% and specific molar ratios of alkali activators. Additionally, the model is effective only when the sodium hydroxide (NaOH) concentrations are between 8M and 12M. This limitation indicates that while the model is robust within these parameters, its predictions might not be accurate if the conditions deviate from these specified ranges.

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