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*Original article*

# Predicting the Dry Density of Clay Soil Improved by Adding Glass Powder Using a Back Propagation Neural Network Model

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## ABSTRACT

*Clay soil has undesirable engineering properties, which can compromise structural stability. This study aims to enhance the compaction properties of high-plasticity clay soil by adding glass powder using artificial intelligence (AI), specifically through the Back propagation Neural Network (BPNET), to accurately predict dry density. The model used influential factors, such as wet soil weight (Wnet), glass powder ratio (Wglass), and water content (ω %) as inputs, with dry density (γ) as the output. The model demonstrated high accuracy, achieving a Mean Squared Error (MSE) of 0.0000117 and a Mean Absolute Error (MAE) of 0.002849, reflecting its effectiveness in improving clay soil properties and supporting its stability.*

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## INTRODUCTION

Clay soil is known for its undesirable engineering properties, as it suffers from low shear strength and high susceptibility to settlement under continuous loads. Due to changes in moisture content, this soil can expand and shrink significantly, adversely affecting the stability of structures. Therefore, soil stabilization is a vital process to improve its engineering properties .Soil maintenance requires enhancing its efficiency to ensure the safety and effectiveness of construction projects. If the soil is unsuitable, its properties can be modified to meet design requirements using appropriate stabilization techniques based on soil type and site conditions [1,2].

Abdelrahman, S. A., and colleagues studied the use of glass powder as an environmentally friendly alternative for stabilizing clay soil, focusing on its compaction properties. They tested various proportions of glass powder—0%, 5%, 10%, 15%, and 30%—added to high-plasticity (C-H) clay soil according to ASTM-USCS standards. The researchers used gradian of glass powder as well graded sand passing through 0.15 mm sieve. The results showed that adding 5% glass powder significantly improved the soil's properties, with further increases continuing to enhance performance when combined with well-graded sand. These findings confirm the effectiveness of glass powder as a stabilizing material for clay soil [3].

Improving the compaction properties of soil is essential, as it directly affects the load-bearing capacity and strength critical for the design of geotechnical structures. One effective method for enhancing clay soil properties is the application of artificial intelligence, particularly artificial neural networks (ANNs), including back-propagation neural networks (BPNET). These algorithms enable rapid and accurate data analysis, allowing for the efficient determination of optimal soil properties. ANNs are advanced techniques in artificial intelligence, with the Back Propagation Neural

Network (BPN) capable of approximating any function through its nonlinear architecture. This capability makes it applicable in various engineering contexts [4,5]

Many researchers indicate that ANN models demonstrate efficiency in accurately predicting soil properties.

Mahmood Al-Janabi employed a back-propagation neural network (BPN) model to predict the ultimate bearing capacity of shallow foundations on non-cohesive soils, utilizing data from 97 load tests with five key input factors. The findings revealed that the BPN model surpassed traditional theoretical methods, demonstrating its effectiveness in estimating bearing capacity for engineering applications [6]

Nagis H. emphasizes that artificial neural networks (ANN) serve as a valuable tool for estimating soil compaction properties based on textural characteristics. A study tackling the challenges of soil penetration resistance (SPR) developed ANN models for optimal moisture levels, relying on measurements from 280 points and 324 samples. The most effective model, derived from sand and clay content, achieved a mean squared error (MSE) of 0.0029, highlighting the efficacy of ANN in estimating soil properties [7].

This study employs Back Propagation Neural Network (BPNN) algorithms to enhance the accuracy of predictions concerning the compaction properties of high-plasticity clay soil. The aim is to deliver sustainable and precise solutions that improve soil performance across diverse construction projects. This paper underscores the significant role of artificial neural networks (ANNs) in the analysis of clay soil data and the prediction of optimal compaction characteristics. By adopting these advanced methodologies, it is possible to achieve greater efficiency, while effectively conserving time and resources, thus reducing dependence on traditional laboratory experiments.

## METHODOLOGY

### *Artificial Neural Network (ANN)*

Artificial Neural Networks (ANNs) effectively model complex problems, especially with noisy or unknown data distributions. An ANN consists of inputs, weights, thresholds, activation functions, and outputs. The aggregator function combines the weighted inputs, while the activation function regulates the output, typically between 0 and 1 or -1 and 1. Back propagation (BP) minimizes the Mean Squared Error (MSE) between actual and target outputs using gradient descent, enhancing prediction accuracy. During verification, the network optimizes training duration, hidden neurons, and learning parameters such as learning rate and momentum. The best-performing networks are selected for further testing, with the highest-performing network used in practical applications. Figure 1 illustrates the ANN model and its components.

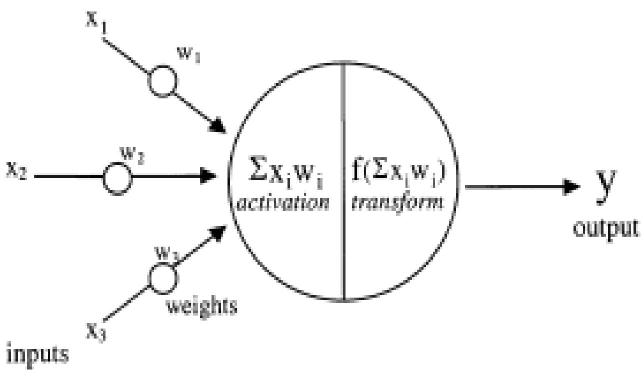


***Figure 1. The basic ANN model [9].***

### *Study Data*

The present study utilized data sourced from a prior experiment published in a research paper by Baraka, S. A., et al. (2018), which investigated the compaction properties of clay soil with the incorporation of glass powder in various proportions: 0%, 5%, 10%, 15%, and 30% of the soil's weight. The dataset included critical factors influencing dry density, such as the wet weight of the soil, the percentage of glass powder, and the water content. These factors were employed as input variables in the analysis, while the output variable was the dry density of the soil, assessed through the application of artificial intelligence techniques.

The data preparation for analysis involved the normalization of datasets to ensure their quality and appropriateness for the back-propagation neural network (BPNET) model. This preparation process entailed the identification of missing data and outlier values, as well as the organization of the data to align with the requirements of the model. The experimental data is presented in Table 1.

*Table 1. The data obtained from the experiments.*

| Real Values | | | | Normalizing Values [0-1] | | | |
|---|---|---|---|---|---|---|---|
| Wnet X1(g) | Wglass X2(g) | ω% X3 | $\gamma$ Y1(g/cm$^3$) | X1 new1 | X2 new1 | X3 new1 | Y1 new1 |
| 1275 | 0 | 16.7797 | 1.16381 | 0.240747 | -1.96437 | -1.93535 | 0 |
| 1386 | 0 | 18.5222 | 1.24653 | 0.432722 | -1.96437 | -1.93234 | 0.22024 |
| 1456 | 0 | 19.8509 | 1.29497 | 0.553788 | -1.96437 | -1.93004 | 0.349208 |
| 1536 | 0 | 23.2243 | 1.32872 | 0.692148 | -1.96437 | -1.92421 | 0.439074 |
| 1568 | 0 | 24.8082 | 1.33919 | 0.747492 | -1.96437 | -1.92147 | 0.466945 |
| 1714 | 0 | 31.6719 | 1.38758 | 1 | -1.96437 | -1.9096 | 0.595774 |
| 1590 | 0 | 36.7356 | 1.23953 | 0.785541 | -1.96437 | -1.90084 | 0.201586 |
| 1572 | 0 | 38.3251 | 1.21141 | 0.75441 | -1.96437 | -1.89809 | 0.126732 |
| 1232.15 | 64.85 | 14.596 | 1.20645 | 0.166638 | -1.85221 | -1.93913 | 0.113531 |
| 1374.65 | 72.35 | 18.2796 | 1.30406 | 0.413092 | -1.83924 | -1.93276 | 0.373416 |
| 1496.25 | 78.75 | 19.9652 | 1.39948 | 0.6234 | -1.82817 | -1.92984 | 0.627447 |
| 1563.7 | 82.3 | 22.5716 | 1.43146 | 0.740055 | -1.82203 | -1.92533 | 0.712612 |
| 1631.15 | 85.85 | 29.1567 | 1.41708 | 0.85671 | -1.81589 | -1.91395 | 0.674309 |
| 1546.6 | 81.4 | 37.2721 | 1.26419 | 0.710481 | -1.82359 | -1.89991 | 0.267252 |
| 1525.7 | 80.3 | 41.2657 | 1.21185 | 0.674334 | -1.82549 | -1.893 | 0.127899 |
| 1135.8 | 126.2 | 12.0192 | 1.2009 | 0 | -1.74611 | -1.94358 | 0.098746 |
| 1239.3 | 137.7 | 15.0023 | 1.27634 | 0.179004 | -1.72622 | -1.93843 | 0.29961 |
| 1422.9 | 158.1 | 19.023 | 1.41593 | 0.496541 | -1.69094 | -1.93147 | 0.671248 |
| 1562.4 | 173.6 | 24.2399 | 1.48946 | 0.737807 | -1.66413 | -1.92245 | 0.867027 |
| 1504.8 | 167.2 | 31.1699 | 1.35876 | 0.638187 | -1.6752 | -1.91046 | 0.519039 |
| 1485.9 | 165.1 | 36.7178 | 1.28725 | 0.6055 | -1.67883 | -1.90087 | 0.328643 |
| 1208.7 | 213.3 | 15.2 | 1.31579 | 0.126081 | -1.59547 | -1.93808 | 0.404641 |
| 1347.25 | 237.75 | 18.49 | 1.4259 | 0.365704 | -1.55318 | -1.93239 | 0.697788 |
| 1455.2 | 256.8 | 22.05 | 1.49522 | 0.552404 | -1.52024 | -1.92624 | 0.882371 |
| 1497.7 | 264.3 | 25.71 | 1.49409 | 0.625908 | -1.50726 | -1.91991 | 0.879348 |
| 1458.6 | 257.4 | 30.49 | 1.40178 | 0.558284 | -1.5192 | -1.91164 | 0.633584 |
| 1405.05 | 247.95 | 35.3 | 1.30231 | 0.465669 | -1.53554 | -1.90332 | 0.368753 |
| 1237.5 | 382.5 | 19.38 | 1.44652 | 0.175891 | -1.30284 | -1.93085 | 0.752692 |
| 1342.2 | 415.8 | 22.19 | 1.53364 | 0.35697 | -1.24524 | -1.92599 | 0.984653 |
| 1364.2 | 436.8 | 24.71 | 1.5394 | 0.395019 | -1.20892 | -1.92164 | 1 |
| 1277.2 | 460.8 | 27.17 | 1.456818 | 0.244552 | -1.16742 | -1.91738 | 0.780118 |

***BPNET Model Design***

A Back Propagation Neural Network (BPNET) was developed to analyze data related to the compaction characteristics of soil. The network features an input layer with three nodes: the first node represents the wet weight of the soil, the second node represents the proportion of glass powder, and the third node represents soil moisture content. In addition to the input layer, the network includes several hidden layers that contribute to enhancing the efficiency and accuracy of predictions. An output layer is also present, which indicates the dry density values of the soil-the final predicted value based on the inputs. The model was trained using 80% of the available data, with a learning rate of $\lambda = 0.4$, aiming to achieve an expected error threshold of 0.001. Figure 2 provides a detailed illustration of the network structure, while Figure 3 depicts the components of the back propagation neural network and its operational mechanism. Furthermore, Table 3 presents the final statistical results of the BPN, reflecting the model's efficiency and accuracy in predicting dry density values based on the input data.

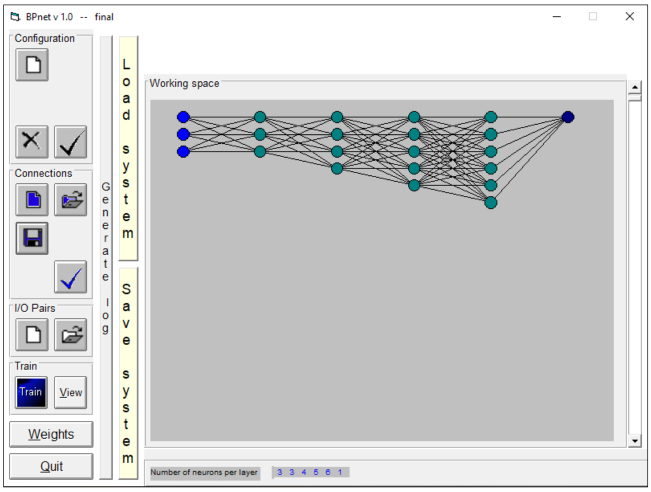


*Figure 2. Stage of building the network.*

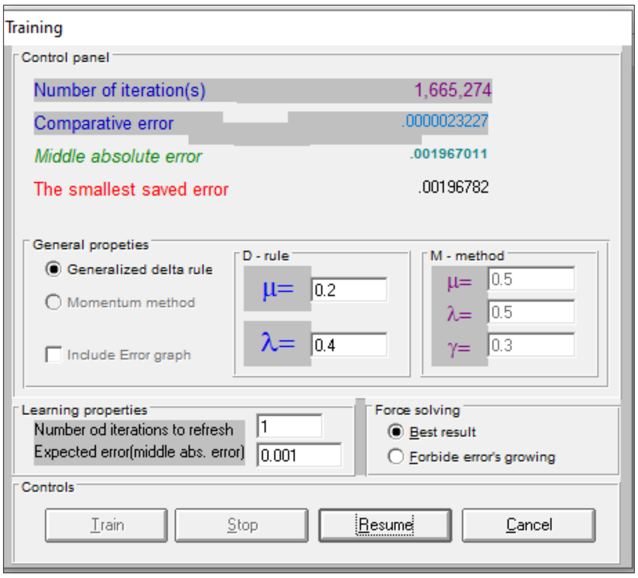


*Figure 3. The neural network with backpropagation.*

*Table 3. Final statistical outcomes of the BPN.*

| Number of Iterations | Comparative Error ($g/cm^3$) | Middle absolute Error ($g/cm^3$) | The smallest Error($gm/cm^3$) |
|---|---|---|---|
| 1665274 | 0.0000023227 | 0.001967011 | 0.00196782 |

## RESULTS AND DISCUSSION

The model with architecture (1 6 5 4 3 3) was utilized for training and testing, employing learning parameters of μ = 0.2 and λ = 0.4, with an error threshold of 0.001. The Back propagation Neural Network (BPNET) demonstrated strong performance in predicting the dry density of clay soil. Model performance was assessed using key error metrics, specifically Mean Squared Error (MSE) and Mean Absolute Error (MAE). Results revealed significant reductions, with MSE at 0.0000117 and MAE at 0.002849, confirming the model’s accuracy and efficiency. These findings indicate the model's effectiveness in learning from data, resulting in reliable predictions of dry density for high-plasticity clay soil. Figure 5 illustrates a predicted BPN output, while Table 4 compares BPN outputs to actual data. Additionally, Figure 6 visually contrasts BPN results with the observed data.

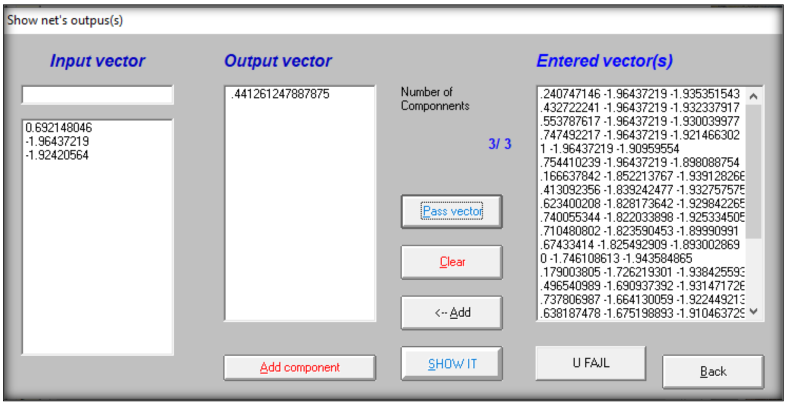


*Figure 5. The predicted value of one of the BPN outputs.*

*Table 4. The forecasted value of the BPN outputs compared to the real data.*

| Real Data | Testing BPN | Error (g/cm3) | square Error | Absolute Value | MSE(g/cm$^3$) | MAE(g/cm$^3$) |
|---|---|---|---|---|---|---|
| **0.439074** | 0.441261248 | -0.002187148 | 4.78362E-06 | 0.002187148 | 1.17E-05 | 0.002849 |
| **0.201586** | 0.203371206 | -0.001785506 | 3.18803E-06 | 0.001785506 | | |
| **0.674309** | 0.675744415 | -0.001435615 | 2.06099E-06 | 0.001435615 | | |
| **0.328643** | 0.329445029 | -0.000802329 | 6.43733E-07 | 0.000802329 | | |
| **0.879349** | 0.884333217 | -0.004984717 | 2.48474E-05 | 0.004984717 | | |
| **0.780118** | 0.786014941 | -0.005897441 | 3.47798E-05 | 0.005897441 | | |

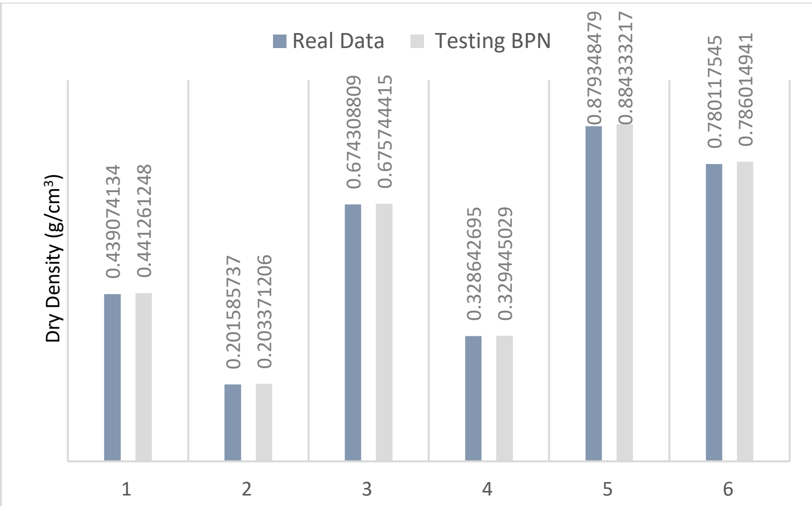


*Figure 6. Real data compared to the BPN output.*

## CONCLUSION

The study successfully developed a Back Propagation Neural Network (BPNET) model to accurately predict the dry density of high-plasticity clay soil, demonstrating the potential of artificial intelligence (AI) to enhance soil stability and efficiency in engineering applications. Evaluation results indicated that the model performed well, achieving low mean squared error (MSE) and mean absolute error (MAE) values, which reflects its high efficiency in predicting soil properties. These findings suggest that AI, particularly neural networks, can offer an innovative approach to improving soil properties and stabilization, thereby increasing the efficiency of construction projects and reducing the dependence on costly traditional methods.

***Conflict of interest***. Nil

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# التنبؤ بالكثافة الجافة لتربة طينية محسنة بمسحوق الزجاج باستخدام نموذج شبكة عصبية ذات الانتشار العكسي

**جلال السنوسي[1] ، فتحية عبد الحميد النعاس[2] ، سميحة عبد الرحمن بركة[2] ، نعيمة محمد[2] ، هبة منصور[2] ، آلاء خالد[2]***

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**المستخلص**
تمتلك التربة الطينية خصائص هندسية غير مرغوبة، مما قد يهدد استقرار الهياكل الإنشائية. تهدف هذه الدراسة إلى تحسين خصائص الدمك للتربة الطينية ذات اللدونة العالية عن طريق إضافة مسحوق الزجاج باستخدام الذكاء الاصطناعي، وبالتحديد من خلال شبكة الانتشار العكسي، للتنبؤ بكثافة التربة الجافة بدقة. استخدم النموذج عوامل مؤثرة مثل وزن التربة الرطبة، ونسبة مسحوق الزجاج، ونسبة المحتوى المائي (ω %) كمدخلات، مع الكثافة الجافة ($\gamma$) كمخرج. أظهر النموذج دقة عالية ، حيث حقق متوسط خطأ تربيعي قدره 0.0000117 وخطأ مطلق قدره 0.002849، مما يعكس فعاليته في تحسين خصائص التربة الطينية ودعم استقرارها.
**الكلمات الدالة**. الذكاء الاصطناعي، نموذج الشبكة العصبية ذات الانتشار العكسي، تربة الطين، مسحوق الزجاج، الكثافة الجافة.