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Evaluation of the Changes in the Strength of Clay Reinforced with Basalt Fiber Using Artificial Neural Network Model

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Abstract: In this research, the impact of basalt fiber reinforcement on the unconfined compressive strength of clay soils was experimentally analyzed, and the collected data were utilized in an artificial neural network (ANN) to predict the unconfined compressive strength based on the basalt fiber reinforcement ratio and length. For this purpose, two different lengths of basalt fiber (6 mm and 12 mm) were added to unreinforced bentonite clay at ratios of 0%, 1%, 2%, 3%, 4%, and 5%, and unconfined compressive tests were performed on the prepared reinforced clay samples to determine the unconfined compressive strength (q_u) values. The evaluation of the obtained experimental results was carried out by creating ANN models. To validate the prediction capabilities of the ANN, a comparative analysis was performed using linear regression, support vector machines, and Gaussian process regression models. Ultimately, a five-fold cross-validation technique was employed to objectively evaluate the overall performance of the model. The evaluations revealed that the ANN model predictions using data obtained from experimental studies showed the highest accuracy and were in close agreement with the experimental results.

Keywords: artificial neural network; basalt fiber; clay; reinforcement; unconfined compressive strength

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1. Introduction

Clayey soils are frequently encountered problematic soils in geotechnical studies. In engineering work on such soils, many challenges arise due to their low strength, high compressibility, and settlement. Soil improvement and reinforcement are among the best alternatives in areas where such soils are present. One of the most effective methods used for many years is additive stabilization, which involves various additives such as fly ash, volcanic ash, volcanic tuff, silica fume, and lime. Due to the increasing costs and demand, and to prevent environmental pollution, researchers have sought materials with superior properties that are more environmentally friendly and easily accessible as raw materials, as technology has developed. Consequently, in recent years, various fibers such as carbon, polymer, basalt, and glass have been studied for this purpose, and research on the use of fibers in soil reinforcement applications has accelerated [1–9]. Among these fibers, basalt fiber is particularly noteworthy. This is because basalt fiber is derived from basalt rock, which forms as a result of the cooling of lava erupted from volcanic activity and is widely distributed in nature, available in large quantities, and naturally occurring. Additionally, its lack of harm to the environment, humans, and living beings, as well as its sustainability and high strength, are among its key features. However, due to their recent emergence, studies on the use of basalt fibers in soil reinforcement applications are still insufficient. In studies conducted on this subject, various geotechnical properties of soils have been examined by using basalt fibers in different proportions and lengths in different types of soils [10–13].

The use of fiber materials in soil reinforcement processes is typically aimed at strengthening the physical properties of the soil matrix and improving soil behavior. In this context, the concept of “cylinder confinement” emerges as an innovative technique in geotechnical applications such as soil support systems, foundations, and slope stabilization, where cylindrical structures within the soil matrix are utilized to enhance strength and stability. Fiber-reinforced soil and cylinder confinement are complementary methods in civil engineering applications. While fiber reinforcements increase the resilience of the soil matrix, the use of cylindrical structures further amplifies the effects of these reinforcements. This combination improves soil behavior, enhancing the safety and durability of structures. Studies on this topic [14–18] indicate that cylinder confinement creates a structure around soil fibers, maintaining them in a specific arrangement. This structure facilitates the effective functioning of the fibers and their interaction with the soil, while the cylindrical form protects the soil fibers against external impacts and increases load-bearing capacity. Additionally, cylinder confinement enables the better distribution of soil fibers under external loads, thereby reducing the risk of cracking or deformation.

The q_u of soils can be determined in laboratories using the unconfined compressive test. However, these tests can often be time-consuming. In experimental studies, the fiber proportions, fiber lengths, and the amount of water used in preparing the mixtures are mostly selected randomly, and optimal values are obtained after performing numerous tests. Since these optimal values may vary in different types of soils, new experimental studies need to be conducted each time. This situation increases both the cost and labor, and, most importantly, it is very time-consuming.

Furthermore, the test equipment may experience wear and tear due to repeated use in these experimental studies. To overcome these challenges, intelligent systems can be implemented to reduce time delays, minimize material waste, and lessen equipment wear, thereby enhancing both the efficiency and sustainability of the evaluation procedure.

To achieve this objective, various intelligent methods are employed for evaluating compressive strength performance, including artificial neural networks (ANNs), fuzzy logic, genetic algorithms, and particle swarm optimization [19–23].

In their study, Ndepete et al. [21] aimed to determine the mechanical properties of basalt-fiber-reinforced silty soils and to identify the optimal ratio and size of basalt fibers on soil properties. To obtain more reliable results, they characterized soil behavior using machine learning models. The results showed that fiber length and confining pressure had a significant effect on the prediction of maximum deviator stress. In the study by Sert et al. [23], mixtures were prepared with 6, 12, and 24 mm long basalt fiber reinforcements in proportions of 1%, 2%, and 3% with five different water contents for clay soils. Additionally, the dataset, consisting of input variables such as water content, fiber length, and fiber ratio, and output variables such as stress and deformation, was modeled using different machine learning algorithms. The results from the machine learning algorithms revealed that the best fit was obtained with Support Vector and Decision Tree Regression.

In the study by Garg et al. [19], the aim was to develop a functional relationship between fiber content, soil density, and soil moisture and the mechanical factor of fiber-reinforced soil for four different fibers (coconut, jute, water hyacinth, and polypropylene). For this purpose, an integrated methodology involving laboratory tests and the Extreme Learning Machine (ELM) technique was used to develop models. Models were developed using ELM to predict the compressive strength of soils reinforced with different types of fibers. The predictive accuracy of the ELM models appeared to be reasonably sufficient for estimating the compressive strength of fiber-reinforced soils. In the study by Tiwari and Satyam [20], the effects of pond ash and polypropylene fiber on soil strength were investigated. Experimental data were processed using an ANN to develop prediction models for mechanical and durability parameters. The results of the ANN modeling excellently predicted the mechanical properties, with the correlation coefficient reaching up to 0.96. In the study conducted by Sungur et al. [22], the shear strength of clay soil reinforced with glass fiber was predicted using ANFIS (Adaptive Neuro-Fuzzy Inference System). For this purpose, experimental samples with different water contents (13%, 15%, and 17%) and different glass fiber ratios (0%, 1%, 1.5%, and 2%) were prepared. The examination of statistical parameters showed that the ANFIS model provided the best results in predicting shear strength when the data were split into 80% for training and 20% for testing.

Alisha et al. [24] focused on using ANNs to model soil characteristics, enhancing the prediction accuracy of engineering properties such as soil moisture content and compressive strength, thus reducing the need for extensive experimental testing. A different study explored the use of machine learning models such as ANN for predicting the mechanical properties of concrete [25]. It highlighted the benefits of using ANN in comparison to traditional methods for faster and more accurate predictions of compressive strength.

In this study, the effects of basalt fiber reinforcement on the q_u of clay soils were experimentally investigated, and the obtained data were used in an ANN to estimate the q_u value according to the basalt fiber reinforcement ratio and length.

Following a comprehensive experimental investigation, q_u results were derived from the data collected during the experiments. The primary objective of this research is to enable the estimation of q_u for mixtures reinforced with basalt fibers of varying lengths and proportions without the need for additional experimental work, and to determine the optimal basalt fiber reinforcement ratio and length.

By using ANNs, researchers can significantly reduce the time typically required for experimental procedures, thus eliminating the delays associated with waiting several days for the determination of compressive strength. This is particularly beneficial in scenarios where rapid assessments are crucial, such as in construction, geology, and materials engineering, where timely decision-making can impact project timelines and costs. For these reasons, ANNs are preferred in many disciplines such as structural engineering, civil engineering, and geological engineering [26–31].

Although artificial neural networks have been successfully applied in many disciplines such as structural and civil engineering, studies on the use of fibers in soil reinforcement applications are more recent.

In this study, the effect of basalt fiber reinforcement on the unconfined compressive strength of clay soils will be evaluated using an ANN. The study proposes the use of ANNs to evaluate compressive strength, which aims to reduce material waste and save time, instead of conducting numerous experimental tests.

2. Materials and Methods

2.1. Experimental Analysis

In this study, experimental data previously determined by [12,13] were used to predict the q_u of high-plasticity bentonite clay reinforced with basalt fiber. In the conducted studies, the q_u values of both unreinforced and BF-reinforced samples were determined through unconfined compressive tests.

In the study conducted by Aslan Topçuoğlu and Gürocak [12], 6 mm long BF was used in various proportions (1%, 2%, 3%, 4%, and 5%) in bentonite clay. The q_u of unreinforced bentonite clay was determined to be 206.93 kPa through unconfined compressive testing. It was found that the strength values of the bentonite samples reinforced with different proportions of BF ranged between 200.03 and 237.48 kPa. The findings of the study revealed that the highest strength was achieved with a 4% basalt fiber content in bentonite clay reinforced with 6 mm basalt fibers, and increasing the fiber ratio beyond this point led to a reduction in strength.

In another study conducted by Aslan Topçuoğlu and Gürocak [13], 12 mm long BF was used as a reinforcement material in various proportions (1%, 2%, 3%, 4%, and 5%). According to the unconfined compressive test results, the average q_u values of basalt-fiber-reinforced samples ranged between 202.74 and 267.66 kPa. The study's results demonstrated that the peak strength was achieved with a 4% basalt fiber content when 12 mm long basalt fibers were used to reinforce bentonite clay. However, a decrease in strength was observed in the sample containing 5% basalt fiber.

In both studies, the basalt fiber lengths varied, while the BF reinforcement ratios remained the same. Each mixture with 6 mm and 12 mm long fiber reinforcement in bentonite clay was compacted at the optimum water content of unreinforced bentonite, and cylindrical samples were prepared. The mixture ratios used in the experimental studies and the average q_u values are presented in Table 1.

Table 1. Mixture ratios used in the experimental studies and unconfined compressive test results [12,13].

Fiber Length (mm)	Sample Name	B (%)	BF (%)	Average q_u (kPa)
6	B	100	0	206.93
	B + %1BF	99	1	210.24
	B + %2BF	98	2	220.44
	B + %3BF	97	3	226.50
	B + %4BF	96	4	237.48
	B + %5BF	95	5	200.03
12	B	100	0	206.93
	B + 1% BF	99	1	223.64
	B + 2% BF	98	2	229.00
	B + 3% BF	97	3	247.42
	B + 4% BF	96	4	267.66
	B + 5% BF	95	5	202.74

B: bentonite clay; BF: basalt fiber.

In the first phase of the experimental studies, BF was separated with the help of a compressor and added to bentonite clay dried in an oven at 105 °C for 24 h, and then mixed. Subsequently, distilled water was added to these prepared mixtures by spraying at the optimum water content, and they were mixed both manually and with a mixer until a homogeneous mixture was obtained. This was carried out to prevent fiber clumping and aggregation. The mixing time was set to 10 min to ensure a homogeneous mixture. In these prepared mixtures, Proctor tests were performed using a fully automatic soil compactor to compact the samples. Then, cylindrical samples with a height twice their diameter were taken from the Proctor mold, and unconfined compressive tests were performed. As a result of the experimental studies, a total of 60 different q_u values were obtained, and the average q_u values were determined for each mixture.

2.2. Artificial Neural Network

Artificial intelligence (AI) is a scientific discipline aimed at improving computers' ability to carry out tasks such as learning, resolving complex challenges, and making informed choices by emulating human cognitive processes [32]. AI is applied across numerous sectors, including healthcare, the military, and engineering.

There are various AI algorithms, each designed with specific technical characteristics and intended uses [33]. Frequently utilized AI models encompass ANN, LR, SVM, and Gaussian Process Regression (GPR) approaches. GPR is a probabilistic, non-parametric approach that provides flexible predictions with uncertainty estimations, particularly useful in smaller datasets. SVMs are powerful for classification and regression tasks, maximizing the margin between classes for clearer separability, especially in high-dimensional spaces. Simple and interpretable, LR models linear relationships between input and output, best suited for problems where a linear approximation is sufficient.

In this study, data obtained from the experimental research were utilized with different AI algorithms, ultimately proceeding with an ANN that yielded the most favorable results.

The ANN is an intelligent technique that mimics biological neural networks and operates similarly to them [30]. The ANN method processes input data and generates optimal decisions based on predefined conditions. It is particularly effective for addressing nonlinear problems, offering practical, straightforward, and rapid solutions [34]. Due to these attributes, ANNs are gaining popularity across various engineering fields, including geotechnical engineering [29–31,35–37].

This growing use of the ANN approach shows its adaptability and effectiveness in solving complex problems, making it a valuable tool for engineers. Its ability to learn from data and adjust to different situations improves its performance, indicating that its importance in engineering will likely increase as technology progresses.

The framework of the ANN comprises input, output, and hidden layers. The hidden layers serve as intermediaries, facilitating the connection between the input and the output layers. Data entered into the input layer undergo processing by the neurons in the hidden layer before being relayed to the output layer, thereby highlighting the critical role of the hidden layer in information transfer. In more intricate network configurations, the number of hidden layers may be expanded to augment the learning capacity. However, this enhancement can also lead to greater complexity and longer execution times for the network [32]. Thus, the optimal number of hidden layers is contingent upon the network's overall design. In this investigation, a single hidden layer was found to be adequate for attaining the desired outcomes, given the characteristics of the network.

A segment of the input data is employed to develop samples for the purposes of training, testing, and validation. These samples undergo training using diverse techniques, allowing the ANN to produce outputs corresponding to specific inputs under defined conditions.

The experimental data obtained are organized in the lookup tables for utilization within the ANN system. The variables of clay ratio, basalt fiber ratio, and basalt fiber length serve as inputs, while the ANN produces an output. Accordingly, the corresponding q_u value is calculated using the ANN method based on the provided input values. The ANN system employs 3 inputs, 20 hidden neurons, and 1 output, as illustrated in Figure 1.

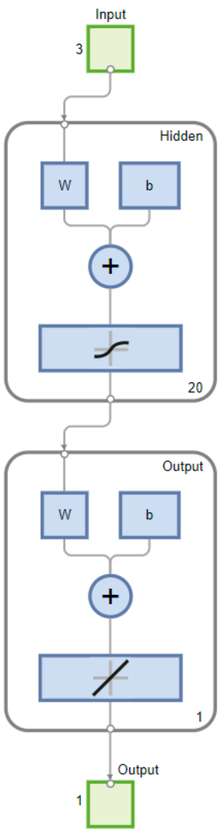

Figure 1. ANN diagram implemented in the system.

3. Results and Discussion

This investigation utilized 60 experimental data points for each of the three input variables. Among these data points, 42 samples (70%) were designated for training purposes, 9 (15%) were reserved for validation, and the final 9 (15%) were assigned for testing. The Levenberg–Marquardt method was selected as the training method for ANN.

The framework of the ANN system designed to evaluate the q_u performance is depicted in Figure 2.

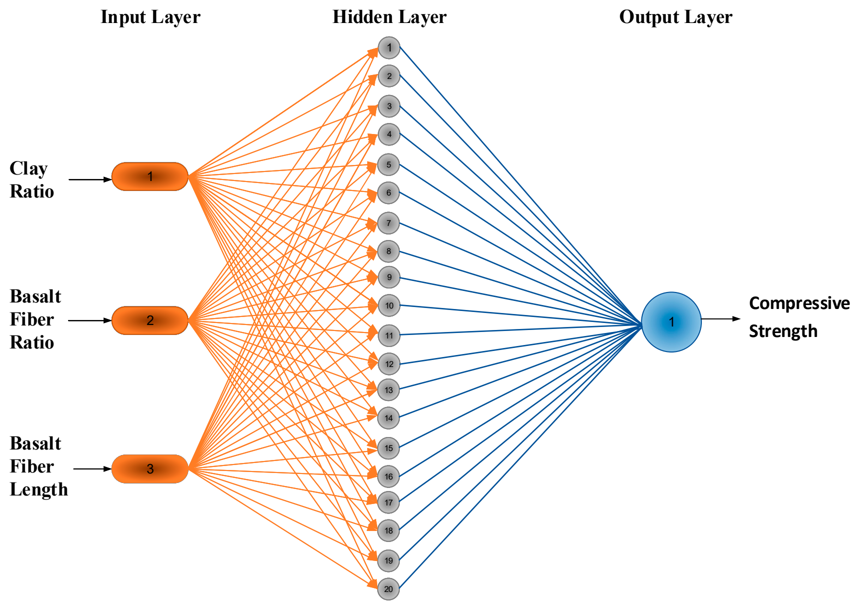

Figure 2. The ANN architecture.

Figure 3 illustrates the Simulink block diagram representing the ANN results for the provided sample input values.

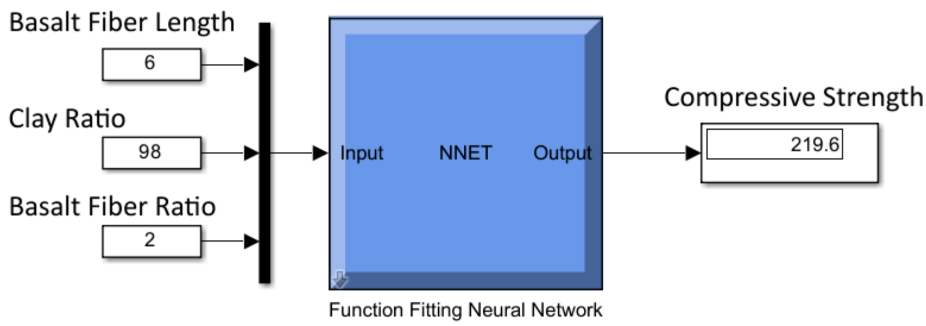

Figure 3. ANN outputs corresponding to sample input values.

The efficacy of the ANN is measured using different metrics. The regression (R) values represent the extent of concordance between the actual data and the outputs generated by the model. An R value close to 1 indicates excellent performance. Given that the outputs from the ANN closely correspond with the experimental findings, the R values are consistently observed to be near 1. Another metric, Mean Squared Error (MSE), is the average of the squared differences between the predicted and actual values. MSE numerically represents the model's error level; lower MSE values indicate a more successful predictive performance. While R serves as a measure of accuracy, MSE is used to evaluate the error rate of the model.

Figure 4 illustrates the R values for the training, validation, test, and overall datasets. Upon analyzing the ANN results alongside the experimental data, it becomes evident that the ANN predictions exhibit a strong correlation with the experimental outcomes. Specifically, R values of 0.95, 0.95, 0.97, and 0.95 were recorded for the training, validation, test, and overall datasets, respectively.

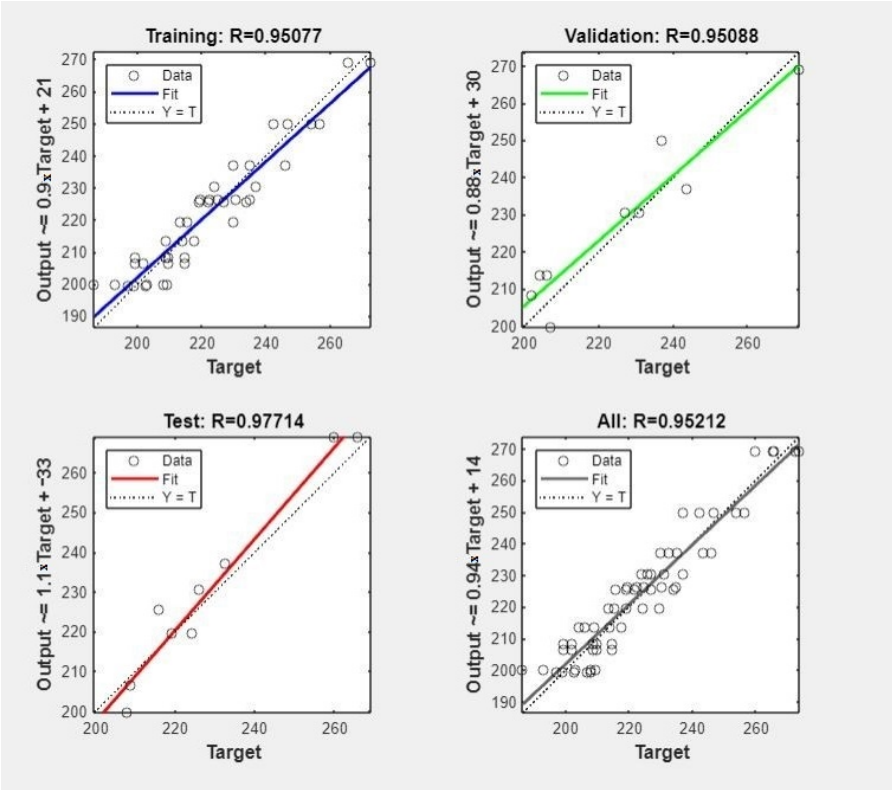

Figure 4. The R values for training, validation, test, and all datasets.

To assess the effectiveness of the ANN model, experimental input values and their corresponding output values generated by the ANN were documented and summarized in Table 2 for comparative analysis. A thorough examination of Table 2 reveals that the ANN outputs closely align with the experimental findings. Consistent with the experimental results, the maximum compressive strength was observed with the incorporation of 4% basalt fiber for both 6 mm and 12 mm basalt fiber lengths, as highlighted in bold in Table 2.

Table 2. Comparison of experimental and ANN outputs.

Sample	Inputs			Experimental Output	ANN Output
	Basalt Fiber Length	Clay Ratio	Basalt Fiber Ratio		
1	6	100	0	206.93	208.20
2	6	99	1	210.24	213.60
3	6	98	2	220.44	219.60
4	6	97	3	226.50	226.50
5	**6**	**96**	**4**	**237.48**	**237.10**
6	6	95	5	200.03	200.00
7	12	100	0	206.93	206.50
8	12	99	1	223.64	225.60
9	12	98	2	229.00	230.50
10	12	97	3	247.42	250.00
11	**12**	**96**	**4**	**267.66**	**269.10**
12	12	95	5	202.74	199.60

Considering the fiber length and fiber ratios used as input parameters in this study, it was determined that the q_u values increased as the fiber length increased, and the 12 mm fiber reinforced samples had higher strength. It was also determined that the q_u values increased as the fiber ratio increased, but this increase continued up to 4% fiber ratio. These results show that fiber length is more effective in increasing strength.

Following this, the ANN was re-evaluated using experimental data. When the predicted values obtained from the ANN were compared with the experimental results, an R value of 0.99 was observed. The regression plot corresponding to the testing process is presented in Figure 5.

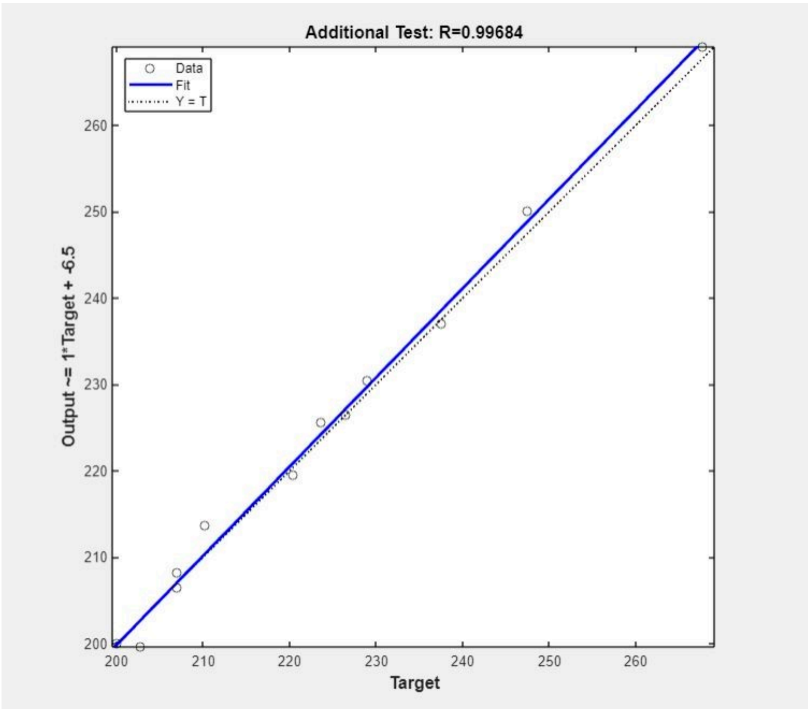

Figure 5. The test regression plot.

To demonstrate the predictive accuracy of the ANN model, a comparison was made with other AI models, including GPR, SVM, and LR. As shown in Table 3, the ANN model produced the best R and MSE value, indicating that it outperformed the other models.

Table 3. Evaluation of R values among different AI models.

	NN	GPR	SVM	LR
R Value	0.90	0.88	0.87	0.68
MSE Value	0.14	0.16	0.17	0.60

As can be seen in Table 3, both the ANN and GPR models demonstrated close performance in predicting compressive strength. The decision to choose the ANN model in this study is due to its high flexibility, complexity in data, and ability to capture nonlinear relationships. This capability is especially valuable in predicting compressive strength, where various factors interact in nonlinear ways. Additionally, ANNs are more scalable with larger datasets, allowing them to refine and improve predictions as more data become available. ANN models are also more robust for applications requiring rapid predictions and can generalize better with diverse, complex input conditions typically seen in compressive strength studies. In contrast, GPR, while effective, can become computationally intensive with larger datasets, making it less practical for extensive applications.

The question of the model's generalizability to real-world data and its reliability is a critical consideration. Consequently, a cross-validation strategy is employed [38,39]. This approach not only mitigates the risk of training a model that is overly reliant on the specific dataset, but also facilitates the assessment of the model's generalizability.

In the cross-validation technique, the dataset is partitioned into smaller subsets, with each subset alternately functioning as the test set while the remaining subsets are used for training. The model undergoes training on the training subsets and is then evaluated on the specified test set. This procedure is reiterated for each iteration of the cross-validation process. The performance metrics derived from each iteration are subsequently consolidated and averaged to compute the total efficacy of the system.

In this research, a five-fold cross-validation approach was employed to impartially assess the model's performance. Consequently, the model's R value was calculated as 0.90. Figure 6 displays the results and depicts the optimal error rate between the predicted data obtained from system output using the five-fold cross-validation and the actual values.

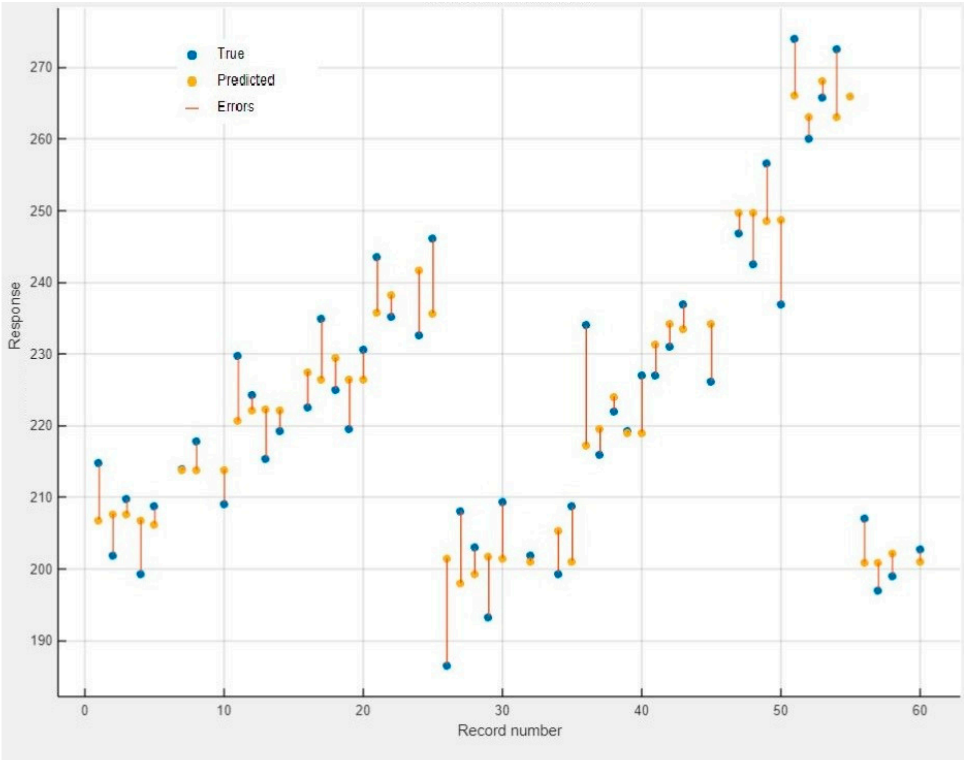

Figure 6. Five-fold-cross-validation response plot.

4. Conclusions

In this study, an ANN model was developed to predict the q_u of clayey soil reinforced with basalt fibers and to determine the optimal fiber length and ratio that provide the greatest increase in q_u. For this purpose, previously published data from experimental studies involving bentonite, a highly plastic clay, were utilized. The q_u values were obtained from mixtures of bentonite reinforced with basalt fibers at varying lengths (6 mm and 12 mm) and proportions (1%, 2%, 3%, 4%, and 5%). The q_u values obtained after the experimental study were evaluated using the ANN. The compressive strength values predicted by the ANN closely matched the experimental results, demonstrating the effectiveness of the ANN in evaluating compressive strength performance.

The ANN methodology enables the quick estimation of q_u for known mixing ratios at different curing ages without the need for preliminary experiments. This capability not only streamlines the evaluation process, but also enhances efficiency and reliability in predicting material performance. As a result, the adoption of ANNs in this context offers substantial advantages in terms of time savings, cost reduction, and labor efficiency. ANNs' scalability, adaptability to complex patterns, and suitability for larger data volumes make them a preferred choice for the model presented in this paper. These advantages will also support potential future research extensions. Ultimately, this study aimed to provide a practical tool for engineers and researchers in the field, fostering more informed decision-making and optimizing resource utilization in geotechnical engineering.

It should be noted that although the optimum basalt fiber ratio and length values obtained from this study can be used for high-plasticity clays used in experimental studies, it will not be appropriate to use them for clays with different engineering properties. The database on this subject can be enriched with new studies to be conducted by changing the basalt fiber contribution ratios and fiber length values in clays with different properties. Similarly, the development of the study is also possible by increasing the number of fiber-reinforced soil series, changing the soil–fiber mixture ratios, or changing the water ratio used in the preparation of the mixtures. In addition, since the success rate of artificial intelligence will increase in parallel with the increase in the number of input data, more experimental results mean more accurate predictions. In addition, deep network architectures can be used to increase the prediction performance obtained as a result of different mixtures used. This study has shown that considering the decrease in soils with suitable geotechnical properties in parallel with the increase in population and structures, the use of basalt fiber, which is sustainable and environmentally friendly and whose raw material is abundant and naturally available in nature, will provide significant gains in soil reinforcement applications.

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