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Application of ANN in Construction: Comprehensive Study on Identifying Optimal Modifier and Dosage for Stabilizing Marine Clay of Qingdao Coastal Region of China

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Abstract: Nowadays, the use of new compound chemical stabilizers to treat marine clay has gained significant attention. However, the complex non-linear relationship between the influencing factors and the unconfined compressive strength of chemically treated marine clay is not clear. In order to study the influence of various factors (dosage, type of stabilizer, curing age) on the unconfined compressive strength of solidified soil during chemical treatment, experiments were performed to determine the unconfined compressive strength of soft marine clay modified with various types of stabilizers. Further, an artificial neural network (ANN) model was used to establish a prediction model based on the unconfined compressive strength test data and to verify the performance. Sensitivity and optimization analyses were further conducted to explore the relative significance of parameters as well as the optimal dosage amount. Research has found that when the content of aluminate cement is 89.5% and the content of curing agent is 30%, the unconfined compressive strength significantly increases after 28 days of solidification, and the change in quicklime content has the greatest effect on the improvement in the unconfined compressive strength. The influence of modifiers on the unconfined compressive strength is in the order: potassium hydroxide > kingsilica > quick lime > bassanite. The values of each factor were obtained when the unconfined compressive strength was the maximum, which provided support for the optimization of the treatment scheme. The analysis of chemical treatment is no longer limited to the linear relationship according to the test results, which proves the feasibility of non-linear relationship analysis based on the artificial neural network.

Keywords: marine clay; chemical treating; artificial neural network; optimization analysis; sensitivity analysis

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1. Introduction

China's coastal area has a complex topography and rich landforms, among which the beach area is very broad. Offshore wind farms are a characteristic of China. For example, offshore wind farms in coastal provinces such as Shandong, Zhejiang, and Jiangsu have been established. The relevant investigation and statistics show that it is of great strategic significance to make full use of resources for wind farm construction and rational and orderly development and utilization. However, most of the offshore wind turbines built in the intertidal zone, which are located in silt sites and have the characteristics of high moisture content, low strength, and a large pore ratio, cannot meet the requirements of the superstructure in terms of strength, deformation, and stability [1–3]. These properties have caused great obstacles to the construction of projects. Therefore, before the construction of a project, it is necessary to treat the silty soil to improve its strength and meet the construction requirements. At present, the chemical curing method can effectively solve the adverse factors of beach silt, which adds an inorganic chemical stabilizer to the beach silt to improve its performance. The traditional solidifying materials for soil are all solid inorganic binders. Good results have been achieved by using lime, cement, and fly ash to improve the soil [4,5]. However, the traditional single chemical stabilizer can no longer meet the engineering needs of beach silt, and the development of a new composite stabilizer has gained significant attention recently. At present, there are abundant research results on chemical curing:

Chew et al. and Porbaha et al. found that the water content of silt would decrease rapidly with the addition of cement, but then it would decrease at a slower rate [6,7]. The larger the curing age, the lower the water content. Lorenzo and Bergado found that the density of solidified soil would increase with an increase in cement content and also curing age [8]. The specific gravity of solidified soil decreases with the addition of cement and has no significant relationship with water content and curing age. Horpibulsuk et al. found that water content not only affects the amount of hydration products during chemical reactions in solidified soil but also has a greater impact on the porosity of 0.1–1 μm [9].

Wang Lifeng [10] used silica nanopowder as an external admixture to be mixed into hydraulic soil and carried out unconfined compressive strength tests on it. The results showed that nanosilica powder can improve the macroscopic mechanical properties of hydraulic soil. Ding Jianwen et al. [11], using the traditional cement curing treatment method based on the use of mixed cement and phosphogypsum joint curing treatment of dredged silt with high water content, reported the results of indoor experiments showing that the effect of phosphogypsum on silt curing soil enhancement is significant, and the amount of this dosage increases with the increase in the initial water content of silt.

Sharma et al. found that the microstructure properties of solidified soil are closely related to the curing scheme [12]. The addition of cement to the stabilizer has a greater effect on the properties of the improved soil than lime. The study showed that the compressive strength of soil samples cured for 28 days was nearly four to six times higher than that of untreated soil samples, reflecting the effect of curing age on strength. Dahal et al. found the maximum strength of the soil by using ordinary Portland cement with different contents [13]. The authors used statistical tools to establish linear relationships between these parameters.

Liu et al. studied the strength characteristics of steel slag, cement, and metakaolin composite (SCM composite)-stabilized soil under different clay contents, water contents, and curing time [14]. SCM composites can effectively improve the strength of solidified soil, and SCM-stabilized soil exhibits similar characteristics as soil-cement. Gong et al. found an efficient stabilizer that could reduce environmental damage through experiments using an eco-friendly stabilizer to solidify soft soil in Nansha [15]. The main component was still cement, but a multi-component stabilizer (18% cement, 3% lime, 4% gypsum, 3% expansive soil, and 0.8% sodium hydroxide) was found to produce the highest strength and curing efficiency.

At present, the research results are still mainly focused on the analysis of the linear relationship between different components and the curing effect in the process of chemical curing according to the test results, and there are few studies on complex non-linear fitting in chemical curing. In recent years, with the rapid development of artificial intelligence technology, machine learning has become an important tool for scientific research and analysis. The dataset for artificial neural network (ANN) modeling is the basis for neural network training, which determines the information that the network can learn and the tasks it can perform. A dataset is usually a set of labeled data that is used to train a neural network to recognize patterns, predict outcomes, or perform classification. Artificial neural network (ANN) dataset parameters mainly include the size, quality, distribution, and labeling quality of the data. Of course, there are some limitations of datasets, such as sample bias, data sparsity, and data imbalance. In this study, an artificial neural network (ANN) model was used, which has the advantages of flexibility in optimization, sensitivity analysis, and risk analysis [16] to solve the fitting of a non-linear relationship between curing strength and different influencing factors [17]. Also, the model analysis was carried out on the results of unconfined compressive strength testing of a set of curing schemes with optimal mix ratio, and the complex non-linear relationship between the dosage of stabilizer components and the unconfined compressive strength was obtained. Further, optimization and sensitivity analyses were conducted to understand the optimum dose and also the ranking of parameters.

2. Materials and Methods

2.1. Sampling and Basic Properties of Marine Clay

The marine clay utilized in this study was collected at the depth of 1–2 m from the vicinity of Hongshiya, Huangdao District, Qingdao City. The geographical location is shown in Figure 1a, and the site is shown in Figure 1b. The surface color of the marine clay was dark brown, while the interior color was black, with fine mud, and an odor. The marine clay soil samples were collected and sealed in plastic buckets. The original state of the marine clay and sampling area of the silt soil sample are shown in Figure 1c,d.

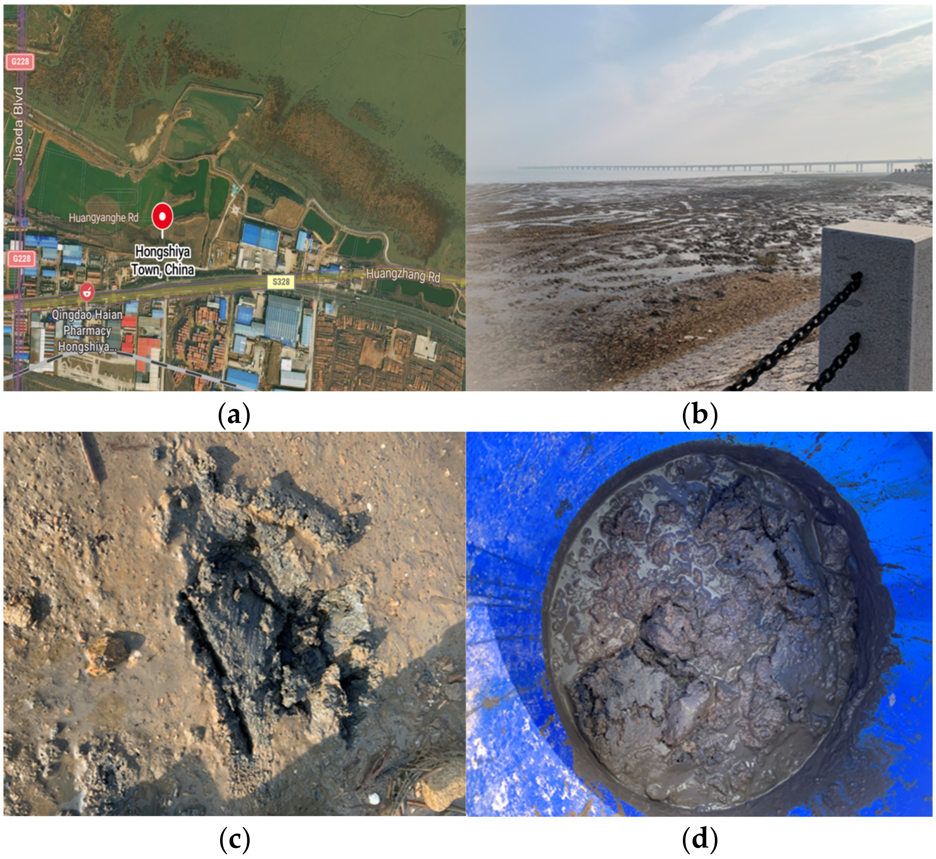


Figure 1. Sampling details. (**a**) Geographical location (Huangdao District, Qingdao City) of sampling points. (**b**) Scene of sampling. (**c**) Original state of marine clay. (**d**) Sampling and preservation of marine clay.

According to the Chinese standard for geotechnical testing (GBT 50123-2019 [18]) and soil testing (NY/T 1121.16-2006 [19]), a series of laboratory geotechnical tests were carried out to determine the natural density, water content, optimum moisture content, pH value, total water-soluble salt content, and other physical and mechanical properties of the marine clay. The maximum dry density of the soil sample was 1.64 g/cm^3, and the optimum water content was 19.8%, which is shown in Figure 2. The physical and mechanical indexes of tidal silt are shown in Table 1.

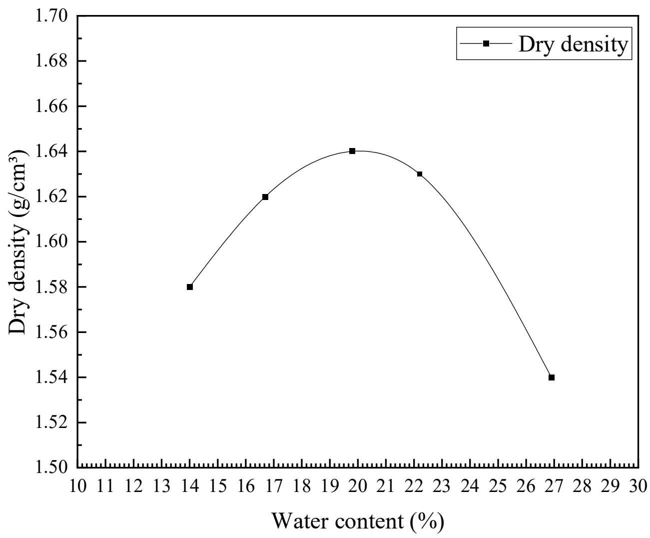


Figure 2. Compaction curve.

Table 1. Basic geotechnical parameters of beach silt soil.

Index	Value
Natural Density, ρ (g/cm^3)	1.68
Moisture Content, ω (%)	120.1
Specific gravity, G_s	2.73
Void ratio, e	1.65
Liquid limit, w_l (%)	83
Plastic limit, w_p (%)	36
pH	8.25
Soil soluble salts, (g/kg)	29.6

2.2. Experimental Details

Chemical treatment of marine clay is achieved by adding a stabilizer to the marine clay, which has the characteristics of high strength, low compressibility, and low permeability [20–23]. Firstly, this section describes the soil solidification treatment measures and the selection of suitable main solidifying agents and additives based on the countermeasure analysis. Secondly, the orthogonal design principle was used to divide different proportion groups of stabilizers. Curing age and dosage of stabilizer were taken as influencing factors for analyzing variations in strength. Marine clay was treated with different proportions of composite stabilizer, the test block was prepared, and the maintenance was carried out. Subsequently, unconfined compressive strength tests were carried out to evaluate the strength of solidified soil blocks under different influencing factors. Finally, the best mix ratio of marine clay stabilizer was obtained, which satisfied the construction requirements of strong stability, high strength, strong bearing capacity, and good compressibility.

2.2.1. Main Stabilizer and Admixture

The main stabilizer used in this study was alumina cement(Zhengzhou Kanghui Refractories Co., Zhengzhou, China). Admixtures included bassanite(Jinan Shengteng Chemical Co., Jinan, China), kingsilica(Shenzhen Haiyang Powder Technology Co., Shenzhen, China), quicklime(Tianjin Zhiyuan Chemical Reagent Co., Tianjin, China), and potassium hydroxide(Jinan Xiaotest Chemical Co., Jinan, China). The components of the stabilizer and their main chemical constituents are shown in Table 2. The composition diagram of the stabilizer is shown in Figure 3.

Table 2. Stabilizer components and their main chemical composition.

Stabilizer Component	Main Chemical Composition
Alumina cement	$3CaO \cdot Al_2O_3$
Bassanite	$CaSO_4 \cdot 0.5H_2O$
Kingsilica	SiO_2
Quick lime	CaO
Potassium hydroxide	KOH

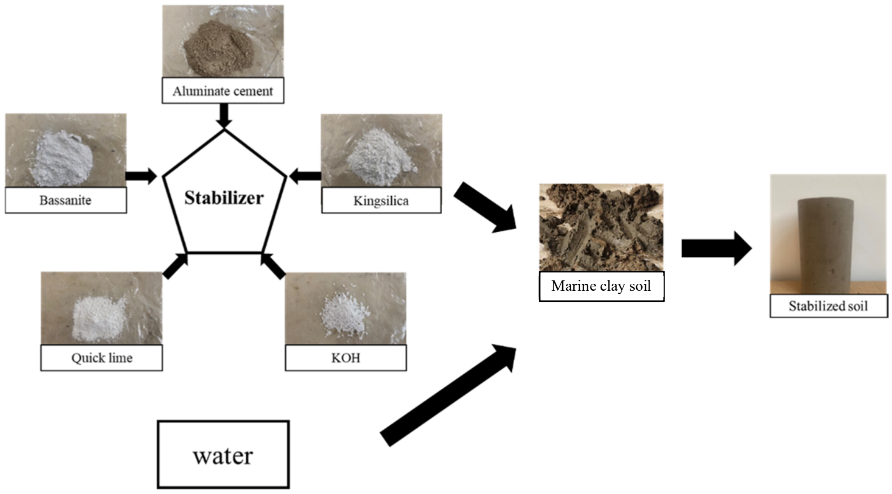


Figure 3. Schematic diagram of the solidified soil production process.

2.2.2. Unconfined Compressive Strength Tests

Water and marine clay were mixed in a ratio of 0.28 by weight. After the mixture reached equilibrium, the main stabilizer and external additives were added to it and uniformly allowed to mix. Firstly, 50 mm diameter and 100 mm high concrete energized volume molds were prepared, and the cured soil was divided into 5–8 layers using the layered manual compaction and molding method, loaded into the molds layer by layer, and manually pounded using a percussion hammer. The prepared specimens were wrapped with cling film and then put into a sealed bag for maintenance to reduce the evaporation of water in the specimens and labeled as a mark. After sample preparation, the mold was removed after 24 h maintenance under natural conditions. The demolded test pieces were wrapped in plastic and placed in sealed bags to prevent any loss of moisture through evaporation. Considering that the basic construction in the intertidal zone needs to be combined with the time of ocean tidal fluctuation, the maintenance age of chemically treated marine clays was increased by 6 h in addition to the conventional 3 or 7 days. The test block was maintained under 95% humidity and 20 ± 5 °C until it reached the maintenance age. The sample was then tested for unconfined compressive strength. The process placed the specimen block on the lower platen and operated the motor to move the key up and down so that the upper pressurized plate just touched the specimen. The data were zeroed manually in the computer terminal, the loading rate of 1 mm/min was entered to start pressurization, and the computer was used to collect the stress–strain relationship data. Similarly, samples under different curing ages and stabilizer dosage factors were tested for compressive strength.

In order to minimize expenditure and also time for conducting the number of tests, an orthogonal test was used for designing the experimental scheme. The test plan based on the orthogonal design approach is summarized in Table 3.

Table 3. Testing plan.

Number	Aluminate Cement Content (%)	Bassanite Content (%)	Kingsilica Content (%)	KOH Content (%)	Quick Lime Content (%)	Solidified Agent Content (%)
0	100	0	0	0	0	
1	95.5	2	1	0.5	1	
2	93.5	2	1.5	1	2	
3	91.5	2	2	1.5	3	
4	91	4	1	1	3	10%
5	92	4	1.5	1.5	1	20%, 30%
6	91.5	4	2	0.5	2	
7	89.5	6	1	1.5	2	
8	89	6	1.5	0.5	3	
9	90	6	2	1	1	

Note: The figures in the table are the mass ratio of each material quality to the solidified agent quality.

The data processing of the unconfined compressive strength tests was performed according to the following formula. The axial strain of the specimens follows the formula:

$$\varepsilon = \frac{\triangle H}{H_0} \times 100 \tag{1}$$

In the formula: ε indicates the strain (%) produced by compression of the test block; ΔH represents the compression (cm); and H_0 indicates the height (cm) of the test block before compression. The average cross-sectional area of the sample follows the formula:

$$A_a = \frac{A_0}{1 - 0.01\varepsilon} \tag{2}$$

In the formula: A_a indicates the corrected area of the sample; and A_0 is the cross-sectional area before compression of the test block (cm^2). The axial stresses on the specimens follow the formula:

$$\sigma = \frac{P}{A_a} = \frac{P}{A_0} \times \left(1 - \frac{\varepsilon}{100}\right) \times 10 \tag{3}$$

In Formula (3): P represents the load produced by the compression of the test block (N).

2.3. Development of Artificial Neural Network Model (ANN)

The artificial neural network model used in this experiment was multi-layer. They were the input layer, hidden layer, and output layer. The input layer consisted of seven nodes, which were the seven factors influencing the unconfined compressive strength of chemically treated marine clay, including the alumina cement content, bassanite content, kingsilica content, potassium hydroxide content, quick lime content, stabilizer content, and curing age. Hidden layers contain functions that transmit and process signals between neurons and their corresponding connections. The output layer had only one node, which was the unconfined compressive strength. The topological structure of the ANN model is shown in Figure 4. In the unconfined compressive strength test of silt-consolidated soil, a total of 90 sets of valid test data were obtained, of which 82 sets of data were used as training for the artificial neural network model, and 8 randomly selected sets were used for the prediction of the neural network model.

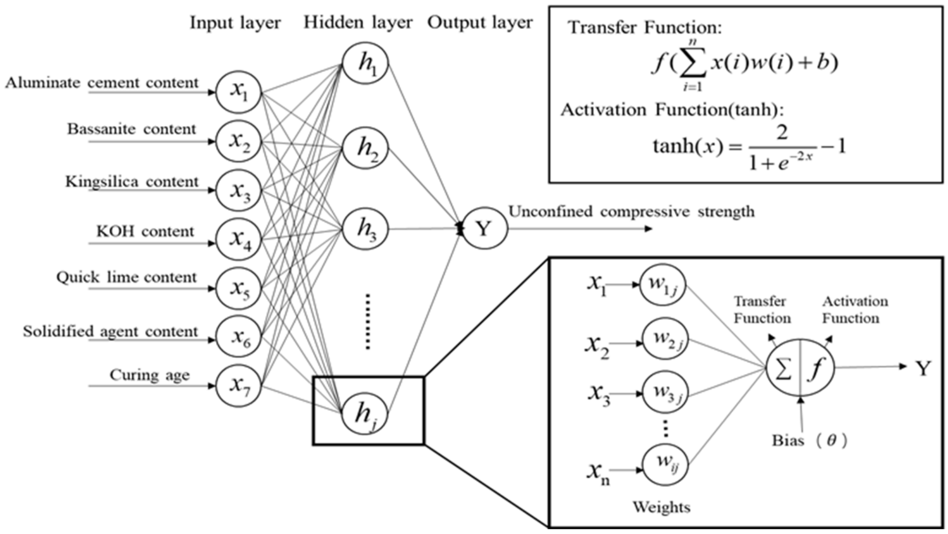


Figure 4. Schematic structure of artificial neural network model.

The operation flow of the ANN model is shown in Figure 5. Data were first normalized using the equation below:

$$X^* = \frac{X - X_{min}}{X_{max} - X_{min}} \quad (4)$$

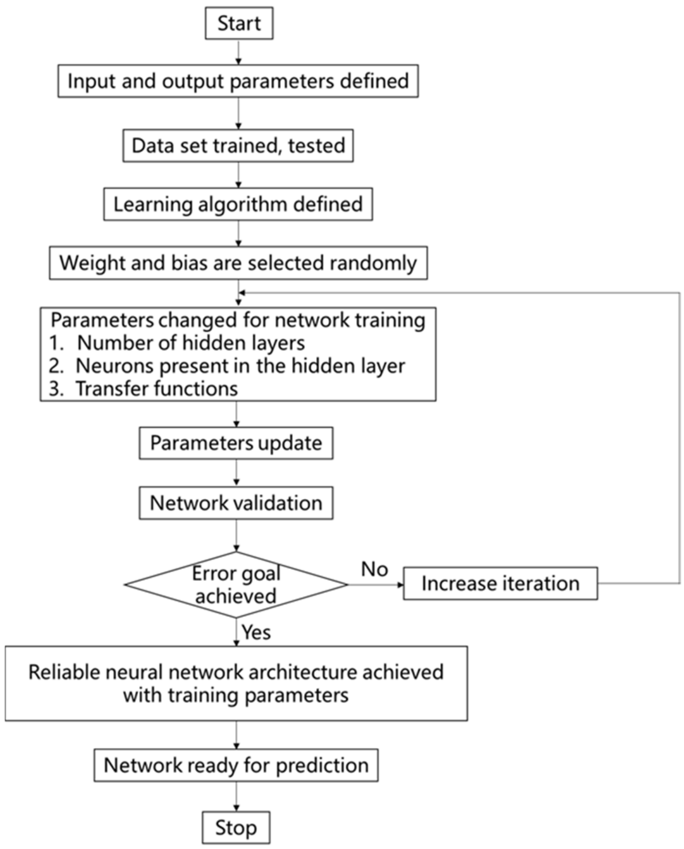


Figure 5. Operation flow chart of the artificial neural network model [24].

In Formula (4): X* is the value after normalization; X is the true value of the raw data; and Xmax and Xmin are the maximum and minimum values of the data, respectively. In this study, all unconfined compressive strength test data collected were divided into 70% training data, 15% validation data, and 15% detection data. In this study, the development of an artificial neural network model mainly used two network forms: multi-layer perceptron (MLP) and radial basis function (RBF). MLP is the most common form of network. Its network is compact and fast to execute, providing better results than other types of networks once trained. However, if these networks require repeated training, the model will run slowly. RBL networks are trained very quickly and are more sensitive to a small number of input variables.

However, RBL often shows relatively poor performance, which is not as effective as MLP networks [23]. In this study, the number of nodes in the hidden layer of the MPL network model selected in the artificial neural network model ranged from 4 to 12.

All data were fitted by the ANN model, and 10 models with a high fitting degree were finally selected. A group of models with MLP 7-8-1 having the highest fitting between the predicted unconfined compressive strength and the actual measured value was selected for subsequent analysis.

Parameter Setting for Optimization Analysis and Sensitivity Analysis

An artificial neural network can fit the proportion of influencing factors when the unconfined compressive strength reaches the maximum, according to the complex non-linear relationship already known. Based on this analysis, the highest strength of chemically treated marine clay can be obtained, and when the strength of chemically treated marine clay reaches the highest value, the amount of hardener added, the proportion of its components, and the age of the curing period can be determined. Through the analysis results, the existing chemical treatment schemes for marine clay can be optimized and improved. In the optimization process, we used the simplex algorithm, the most common and simplest optimization algorithm, to find the maximum value to consider extreme cases. Simplex search is a gradient-free optimization algorithm for minimizing or maximizing any function in a limited number of iterations [25]. A total of 450 iterations were performed for this test optimization analysis.

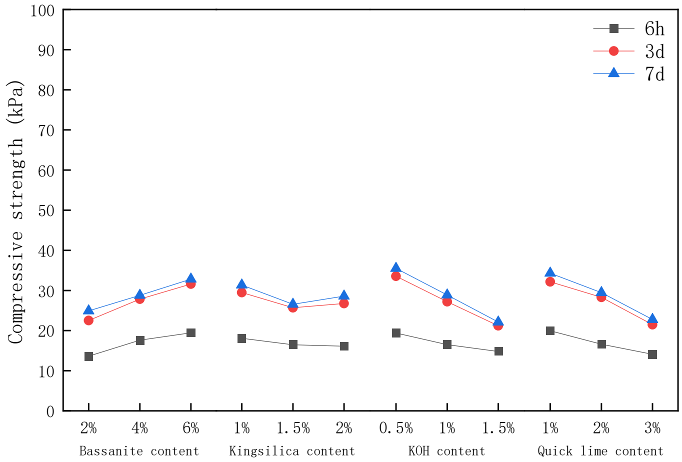
An artificial neural network can also carry out sensitivity analysis on different influencing factors of the input, i.e., quantify the proportion of influencing factors among output results by analyzing the degree of influencing different factors on the output, the unconfined compressive strength. Sensitivity analysis provides a general concept of output sensitivity by changing one input variable while leaving several other input variables unchanged. In this study, we individually changed all influencing factors to study the sensitivity of the unconfined compressive strength with other inputs unchanged.

3. Results and Discussion

3.1. Effect of Chemical Treatment on Unconfined Compressive Strength (UCS) of Marine Clay

In this experiment, two test variables, conservation age and curing agent dosage, were set up to explore the effects of both on the effectiveness of curing agent in curing beach silt. Three gradients of 10%, 20%, and 30% of curing agent dosage were designed for the preparation of test blocks for each proportion group; and three time periods of 6 h, 3 days, and 7 days were set for the routine maintenance of the test blocks. At the same curing agent dosage, 9 samples were tested at each age, totaling 81 samples.

It can be observed from Figure 6a,b that when the content of additives is low (i.e., 10% and 20%), the influence of each additive on the average unconfined compressive strength is minimal at different levels. However, the situation changes significantly when the stabilizer content reaches 30% (refer to Figure 6c). The unconfined compressive strength not only varies significantly with the level of each additive but also increases significantly at different curing ages. Taking 30% stabilizer as an example, the primary and secondary order of influence on the unconfined compressive strength at the curing age of 6 h is quick lime > potassium hydroxide > bassanite > kingsilica. When the curing period is 3 days, the primary and secondary order of influence on the unconfined compressive strength is potassium hydroxide > bassanite > quick lime > kingsilica. When the curing period is 7 days, the primary and secondary order of influence on the unconfined compressive strength is potassium hydroxide > kingsilica > quick lime > bassanite.



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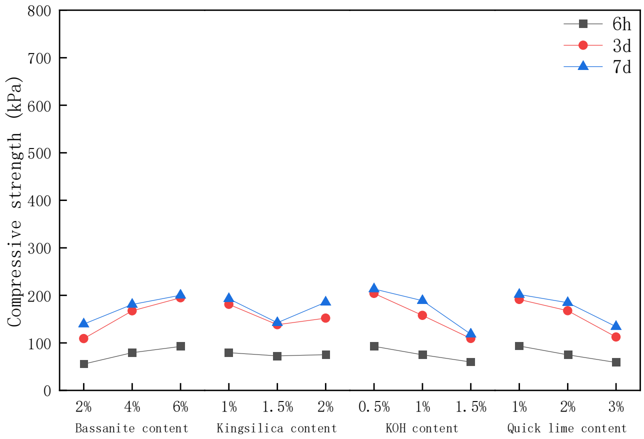

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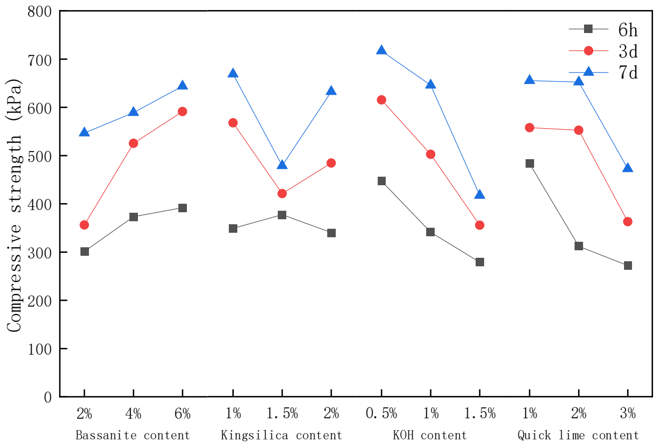


(**c**)

Figure 6. Average unconfined compressive strength of different external admixtures at different levels. (**a**) 10% Stabilizer Content. (**b**) 20% Stabilizer Content. (**c**) 30% Stabilizer content.

At the early stage of treated clay, the main influencing factors of strength are ion exchange of calcium oxide, pozzolanic reaction, and carbonation. It shows that the addition of lime contributes most to the early strength of treated clay. However, with an increase in curing age, there is not enough active aluminum oxide and silicon oxide in the soil to react with lime. In the later stage of solidified soil, its strength is more affected by potassium hydroxide, followed by gypsum and active silicon powder.

Stress–Strain Curve for Unconfined Compressive Strength Tests

The stress–strain curves of chemically treated marine clay samples were obtained through uniaxial compression tests. In order to illustrate stress–strain behavior, testing plan no. 7 was considered due to its superior performance among all other plans. The stress–strain relationship curves of marine clay treated under test plan no. 7 under different stabilizer dosages and curing ages were plotted to analyze the strength and deformation characteristics.

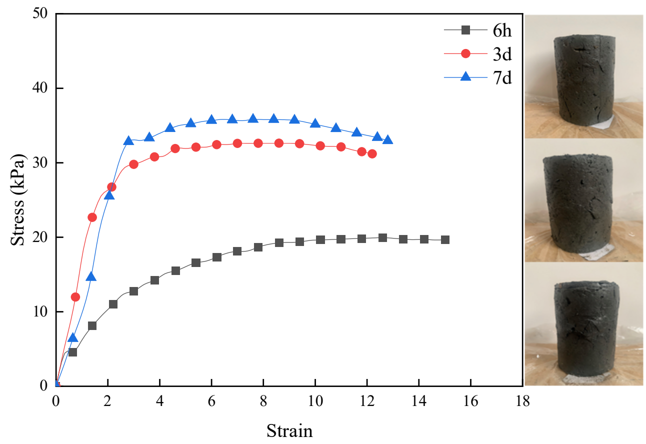
Loading failure of treated clay samples requires three deformation stages: elastic stage, plastic yield stage, and softening stage. The elastic stage is the initial straight-line part of the stress–strain curve, at which the linear relationship between stress and strain is the main stage of stress growth. The compression deformation of the particles in the treated clay is within the elastic range and there is no breakage. The plastic yield stage is the non-linear growth stage of the stress-strain curve. When the strength exceeds the elastic limit stress, the treated clay is gradually damaged, the slope of the stress-strain curve of the solidified soft soil is gradually reduced, the particles inside the sample are broken, and the voids between the soil particles are constantly compacted. At this stage, the effect of soil compaction on the strength increase of the sample is greater than that of particle destruction, and the plastic deformation of solidified soft soil cannot be recovered. Finally, the non-linear downward section of the stress–strain curve is called the softening stage. Cracks in treated clay specimens continue to develop and gradually penetrate, resulting in the failure of the specimens.

As observed from Figure 7, at 10% content, the treated clays at three ages have very low strength and basically show a soft clay state. With the increase in strain, the stress is slowly and gradually elevated without obvious damage peaks, and the elastic phase of the stress–strain curve is short and rapidly enters the plastic phase and the final softening phase. The stress is always below 50 kPa and can hardly withstand pressure. The results show that, at 10% content, the curing effect is not obvious and is unlikely to meet the engineering requirements. It can be observed from Figure 7b that the stress–strain curves for 20% content at the curing age of 3 d and 7 d have gone through three stages. The yield strength reaches about 200 kPa to 250 kPa. However, the elastic phase of the treated clays is still not evident in the specimens at the curing age of 6 h. The results show that the early strength of the stabilized soil is still low when the content of the stabilizer is 20%, which is unlikely to meet the engineering requirements. As observed from Figure 7c, when the stabilizer content is 30%, the treated clay samples can reach a certain strength under the curing age of 6 h, 3 d, and 7 d. The stress–strain curve also completely undergoes the elastic stage, plastic stage, and softening stage. With an increase in curing age, the yield strength increases continuously, up to 830 kPa. The results show that at this optimum mixing ratio, the stabilizer content should not be less than 30% to achieve the full curing effect.

Mixed materials often show non-linear deformation, and the deformation coefficient E50 is often used to indicate the ability of mixed materials to resist elastic-plastic deformation. The definition of the formula is shown in Equation (5):

$$E_{50} = \frac{\sigma_{1/2}}{1/2\varepsilon_f} \quad (5)$$

In the formula: $\sigma_{1/2}$ indicates the strain to destruction in the stress–strain curve of the unconfined compressive strength (%); and ε_f indicates the stress corresponding to half of the breaking strain in the stress–strain curve for the unconfined compressive strength.



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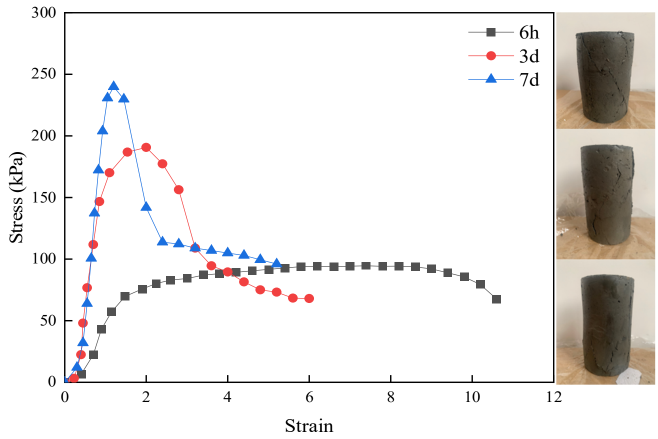

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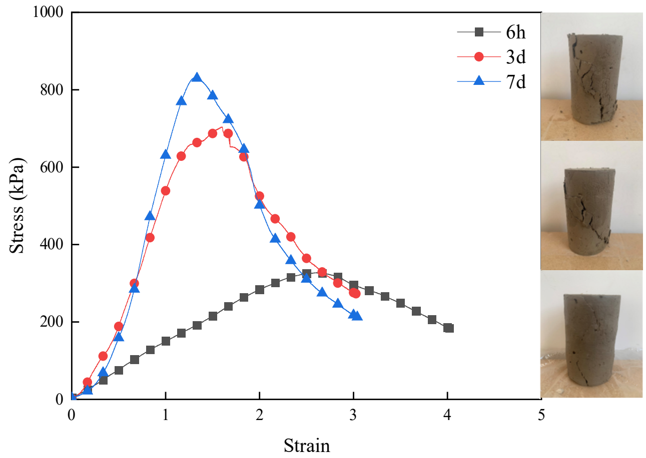

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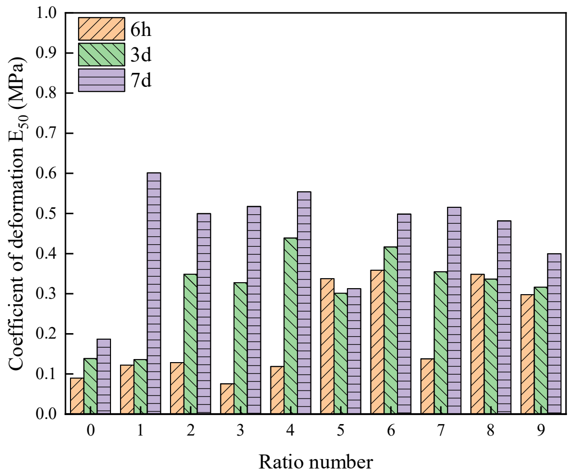
Figure 7. Stress–strain curves of cured soil at different ages with various stabilizer contents. (**a**) 10% Stabilizer content. (**b**) 20% Stabilizer content. (**c**) 30% Stabilizer content.

The deformation coefficients of each group of cured soils at different maintenance ages and curing agent dosage conditions were calculated for comparison, as shown in Figure 8.



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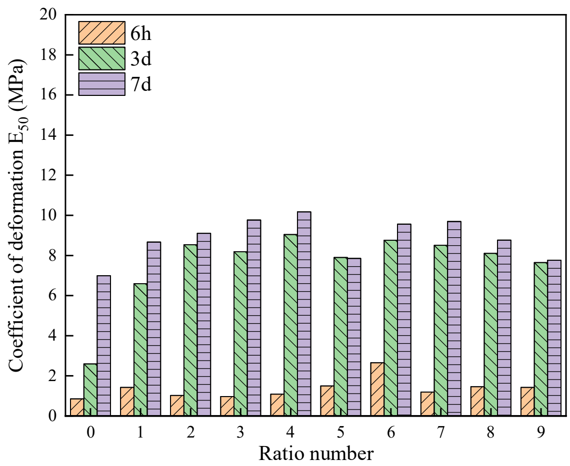

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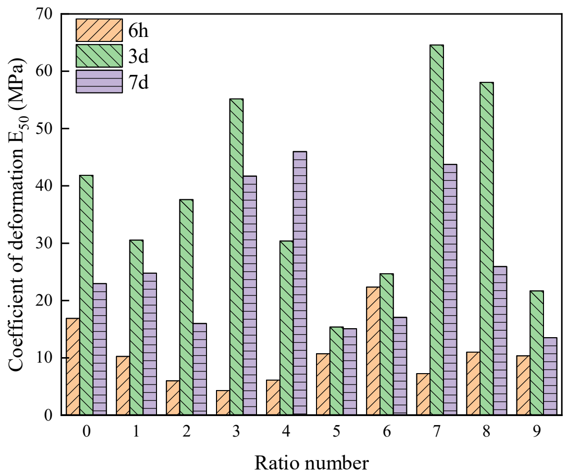

(**c**)

Figure 8. Deformation coefficients of cured soils under different maintenance age conditions. (**a**) 10% Stabilizer content. (**b**) 20% Stabilizer content. (**c**) 30% Stabilizer content.

As can be seen from Figure 8, when the dosage of curing agent is less than or equal to 20%, the deformation coefficient increases with the increase in maintenance age, and the larger the dosage, the more significant the deformation coefficient enhancement effect with the increase in maintenance age, i.e., the stronger the deformation resistance. When the dosage of curing agent is more than 20%, the deformation coefficient increases and then decreases with the increase in maintenance age, and then there is a certain enhancement in the late stage of maintenance, but lower than the deformation coefficient in the early stage, which indicates that the increase in the dosage of curing agent weakens the deformation resistance although the strength will be significantly increased.

3.2. Prediction of Unconfined Compressive Strength Based on the ANN Model

3.2.1. Performance Analysis of Selected Neural Network Model

All original data of the ANN model were fitted, and a group of models with MLP 7-8-1 having the highest fitting between the predicted and measured values was selected for subsequent analysis. The model had 7 input layer nodes, 8 hidden layer nodes, and only 1 output layer node. The performance analysis, optimization analysis, and sensitivity analysis of the above models were used to simulate the unconfined compressive strength of the chemically treated marine clay.

Detailed descriptions of the selected ANN models are summarized in Table 4. The results of artificial neural network training are shown in Figure 8.

Table 4. Detailed description of selected ANN model for UCS tests.

Index	Value
Net. name	MLP 7-8-1
Training perf.	0.984256
Test perf.	0.993253
Validation perf.	0.996300
Training error	0.000947
Test error	0.001037
Validation error	0.012440
Algorithm	BFGS 54
Error function	SOS
Hidden activation	Exponential
Output activation	Tanh

The numbers in rows 2–4 and 5–7 in Table 4 are the fitted regression values and errors of the model in the training, testing, and validation phases, respectively, and they represent the correlation between the output value and the target expectation. When the fitted regression value is closer to 1 and the error tends to 0, it means that the fitting effect is better. As can be seen from the data in Table 4, the model MLP 7-8-1 has a good fit.

It can be observed from Figure 9 that the measured and predicted values are similar to each other, with an R^2 value of 0.992. It should be noted that only the normalized data of each factor is given as input. The ANN model can predict the value of unconfined compressive strength through the existing non-linear relationship. This method can help to replace unnecessary laboratory testing, thereby saving time and expenditure for engineers. It can also achieve the selection and optimization of stabilizers.

In order to verify the authenticity of the predicted results by fitting an artificial neural network, the data which were not involved in model training were randomly selected from the original data. Predicted values from the ANN model were compared with these data. The comparison between the experimental measurements and the network predictions is shown in Figure 10. It can be observed that the predicted value of the model and the measured value of the sample data are very close to each other. An R^2 value of 0.99 is observed.

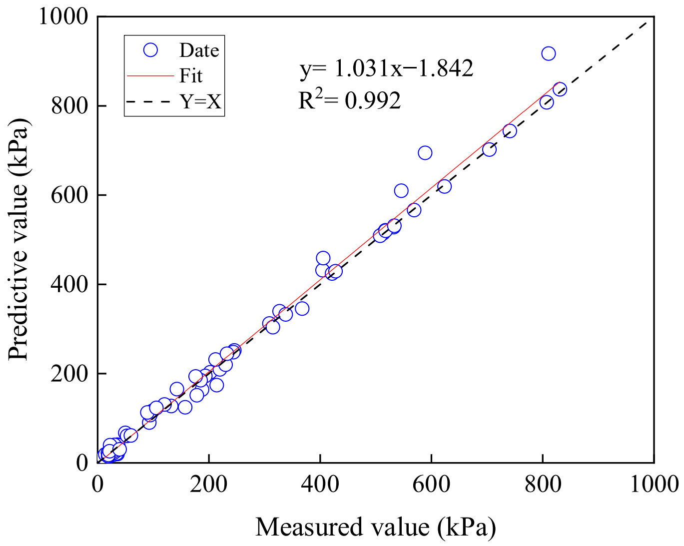

Figure 9. Comparison between measured values and network-predicted values of sample data.

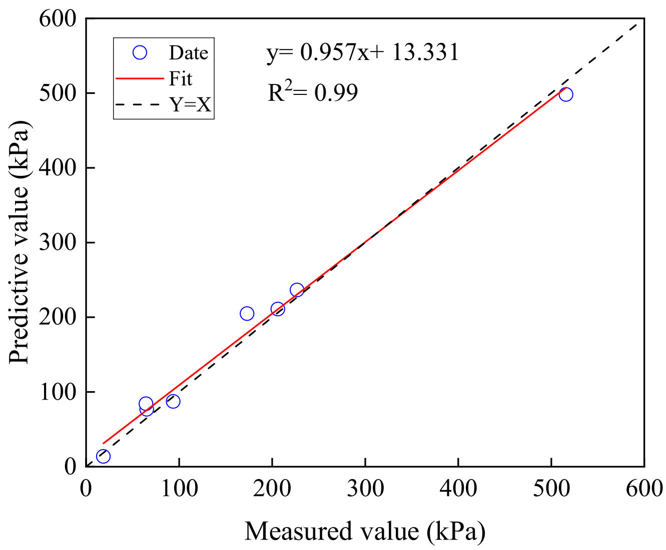

Figure 10. Comparison between measured values (random data not selected for training) and network-predicted values of sample data.

3.2.2. Influence of Different Parameters on Unconfined Compressive Strength

The complex non-linear dependence of one parameter with respect to several parameters can be well displayed in three-dimensional images. As can be seen from Figure 11a,c,e, when the content of potassium hydroxide is about 0.2% and 1.6%, respectively, and the content of gypsum hemihydrate is around 4–6% (Figure 11a); the content of potassium hydroxide is about 0.2% and 1.6%, respectively, and the content of activated silica micronutrient powder is about 2.2% and 1.6%, respectively (Figure 11c); and the content of potassium hydroxide is about 0.6% and 1.6%, respectively, and the lime content is about 0.5% and 3%, respectively (Figure 11e), these parameters together with each other promote the strength of cured soil. With the appropriate amount of potassium hydroxide into the cured soil to improve the pH value, the alkaline environment helps the volcanic ash reaction, and the increase in the content of potassium ions promotes the adsorption and exchange of calcium ions, so that the soil particles flocculate, promoting the dispersion of small soil particles to become larger soil agglomerates, which strengthens the cured soil. But when the content of potassium hydroxide is too much, to a certain extent "robbing" the calcium ions, it reduces the generation of a hydration gel and calcium hydroxide is rapidly consumed without timely replenishment; thus, the strength of the cured soil is weakened to a certain degree.

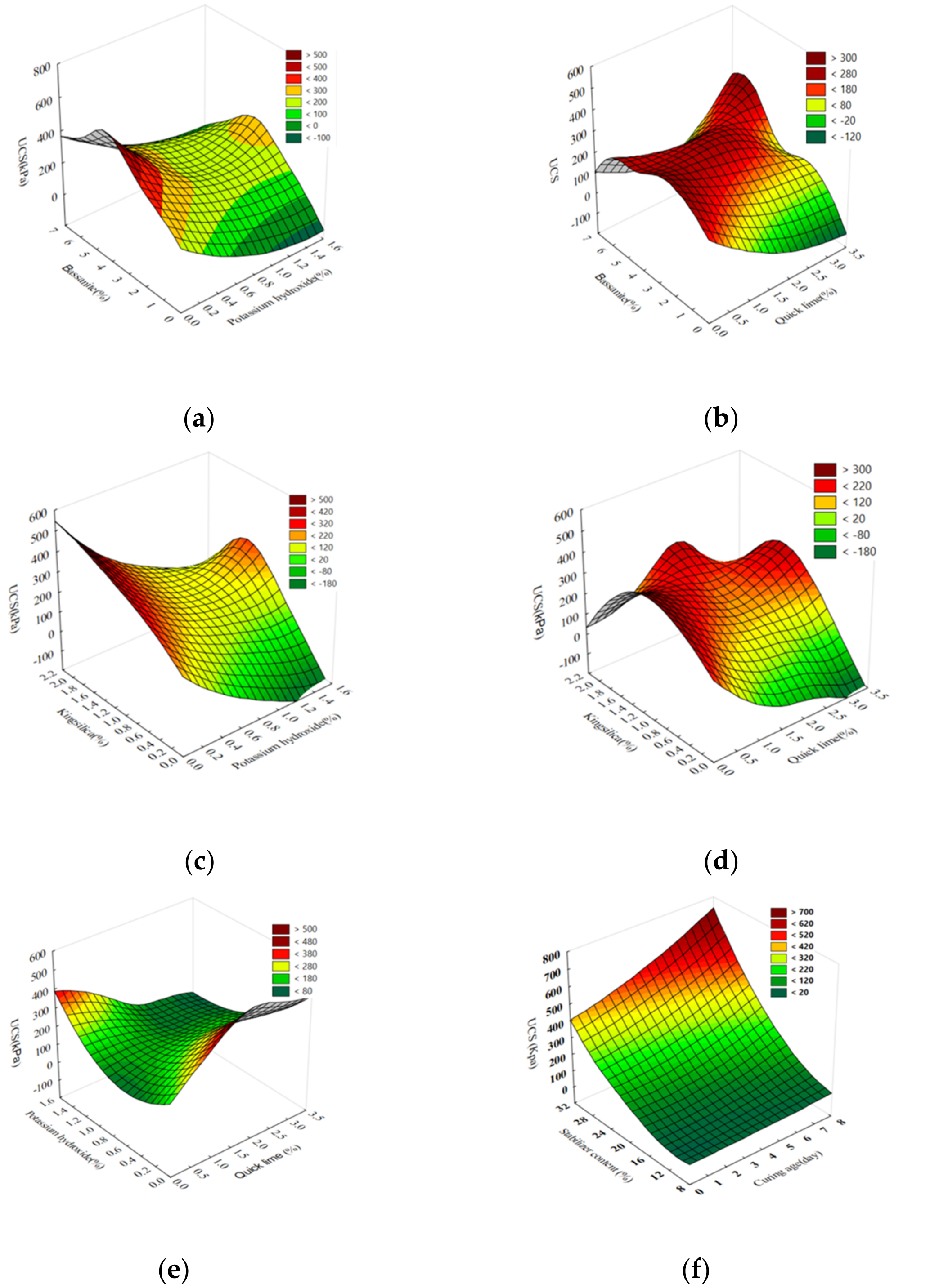

Figure 11. Influence of different influencing factors on unconfined compressive strength. (**a**) Influence of bassanite and potassium hydroxide on unconfined compressive strength. (**b**) Influence of bassanite and quick lime on unconfined compressive strength. (**c**) Influence of kingsilica and potassium hydroxide on unconfined compressive strength. (**d**) Influence of kingsilica and quick lime on unconfined compressive strength. (**e**) Influence of potassium hydroxide and quick lime on unconfined compressive strength. (**f**) Influence of stabilizer content and curing age on unconfined compressive strength.

As can be seen from Figure 11b,d, the interaction of quicklime with hemihydrate gypsum and activated silica micropowder has a significant effect on the unconfined compressive strength of silt-consolidated soil, which is due to the fact that after the calcium oxide, a constituent of quicklime, is dissolved in water, the reaction generates a large amount of $Ca(OH)_2$ that promotes the fracture of the Al–O bond, the Si–O bond, etc., in the hemihydrate gypsum and activated silica micropowder and further reacts to generate the gel substance, i.e., calcium silicate and hydrated calcium aluminate. When the lime content is low, the strength of the cured soil gradually increases with the increase in the content of gypsum hemihydrate and activated silica fume, and then the lime is used as the raw material for the reaction to continue to help the chemical reaction within the cured soil. When the lime content is higher, the strength of cured soil appears to be reduced. Analyzing the reason, too much calcium hydroxide produced by the hydration reaction tends to be saturated, and after saturation, it precipitates in the form of crystals and constitutes a loose structure, which weakens the enhancement of the strength of cured soil. When the contents of activated silica micropowder and semi-anhydrous gypsum exceed a certain range, the chemical reaction "place" within the cured soil is occupied due to the excessive output of hydrated gel material, weakening the degree of reaction, and at the same time, the generation of excessive calcium alumina destroys the internal structure, thus leading to the phenomenon of decreasing the strength of the cured soil.

From Figure 11f, it can be seen that the interaction of stabilizer content and curing age has a significant effect on the unconfined compressive strength of silt-cured soil, but the effect of the stabilizer content on the unconfined compressive strength is more obvious.

3.3. Optimization of Chemical Treatment Technology for Improving the Strength of Marine Clay

3.3.1. Sensitivity Analysis

ANN was used for sensitivity analysis to analyze the relative significance of different factors on the unconfined compressive strength [26–29]. The results of the sensitivity analysis and optimization analysis of ANN are summarized in Table 5.

Table 5. Sensitivity analysis and optimization analysis of ANN.

Variable	Sensitivity Analysis	Optimization Analysis
UCS	-	830 kPa
Aluminate cement content	4.032583	90.06%
Bassanite content	5.186851	3.49%
Kingsilica content	2.998604	2.00%
KOH content	5.807388	0.3%
Quick lime content	30.29768	1.08%
Curing age	2.136436	7 days
Stabilizer content	15.61476	30%

From the sensitivity analysis, it can be observed that the lime content has the greatest influence on the unconfined compressive strength, followed by the stabilizer content. The curing age has the least effect on the strength of treated clay. Due to the large amount of water in sludge, the chemical reaction between lime and pore water in sludge results in hydration as well as physical reactions (ion exchange reaction and calcium hydroxide crystallization reaction). Lime continuously absorbs water to form $Ca[OH]_2 \cdot nH_2O$, which forms crystals that combine and bond with soil particles. Calcium hydroxide reacts with carbon dioxide in the air to produce calcium carbonate. Lime enhances the water stability of the stabilized soil and significantly increases its strength. The change in lime content has a great influence on UCS, which is consistent with the results of the range analysis of the unconfined compressive strength tests. The sensitivity analysis of the ANN model very well showed the influence of each component of the chemical stabilizer. According to the analysis, the proportioning scheme of the stabilizer can be adjusted accordingly to improve the curing effect.

3.3.2. Optimization Analysis

ANN-based models can be optimized and analyzed to find the parameters that can achieve the specific expected results, such as obtaining the maximum unconfined compressive strength in extreme cases and analyzing the values of various influencing factors in this case. The results of the optimal scheme are close to the results of the unconfined compressive strength tests. The results are summarized in Table 5. The maximum convergence diagram of the output results is shown in Figure 12.

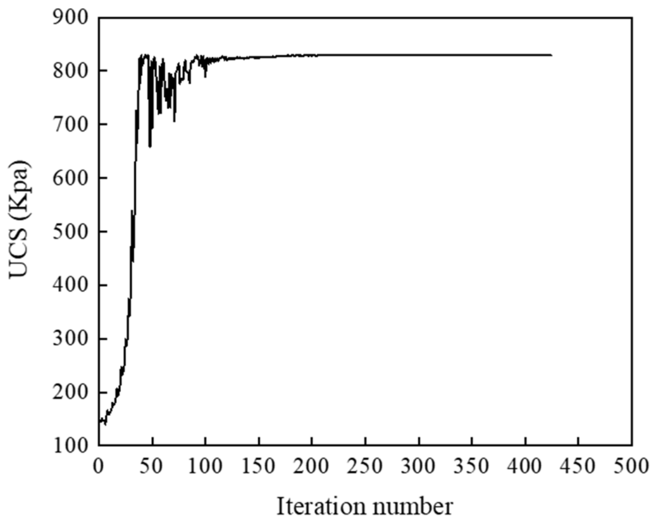

Figure 12. Convergence of maximum output results of unconfined compressive strength tests.

When the number of iterations of the ANN model reaches about 150 times, the unconfined compressive strength converges to the maximum value, which is 830 kPa. When the unconfined compressive strength reaches the maximum value, aluminate cement plays the most important role, with the specific gravity reaching 90.06%. The influence of stabilizer dosage is second, with a specific gravity of up to 30%. It shows that the maximum strength comes from aluminate cement, and the amount of stabilizer is also an important factor to improve the strength of cured soil. On the premise of economy, the amount of stabilizer at 30% tends to achieve the best curing effect. According to this optimization analysis, the dosage and curing age of each component of the stabilizer can be conveniently optimized and reasonably distributed according to the different effects of each factor.

The trend of influence of various factors on the unconfined compressive strength of marine clay can be optimized and analyzed by using the selected ANN model. Figure 13 shows the response curve of the unconfined compressive strength to various influencing factors. The model obtains the maximum unconfined compressive strength by optimizing and analyzing the complex non-linear relationship. At this time, the values of each influencing factor are determined when the maximum UCS is reached and are shown in the diagram.

As can be seen from Figure 13, when only the effect of bassanite is considered, the unconfined compressive strength will first increase and then decrease with an increase in bassanite content. When the content of bassanite reaches about 2%, there is a critical value of UCS, which reaches a maximum of about 828 kPa. It shows that when other factors are set as the current setting values, a small amount of bassanite can improve UCS, while the excessive addition of bassanite will inhibit the curing effect of the stabilizer on beach mud. This is because gypsum reacts with calcium aluminate hydrate in cement hydration products to produce high sulfur-type calcium sulphate aluminate hydrate, i.e., alunite. Aluminum alunite is characterized by volume expansion and can fill the pores of cured soil, thus improving its strength. But excessive addition of gypsum decreases the strength of the stabilized soil because alunite has no cementing effect and only a filling effect [30].

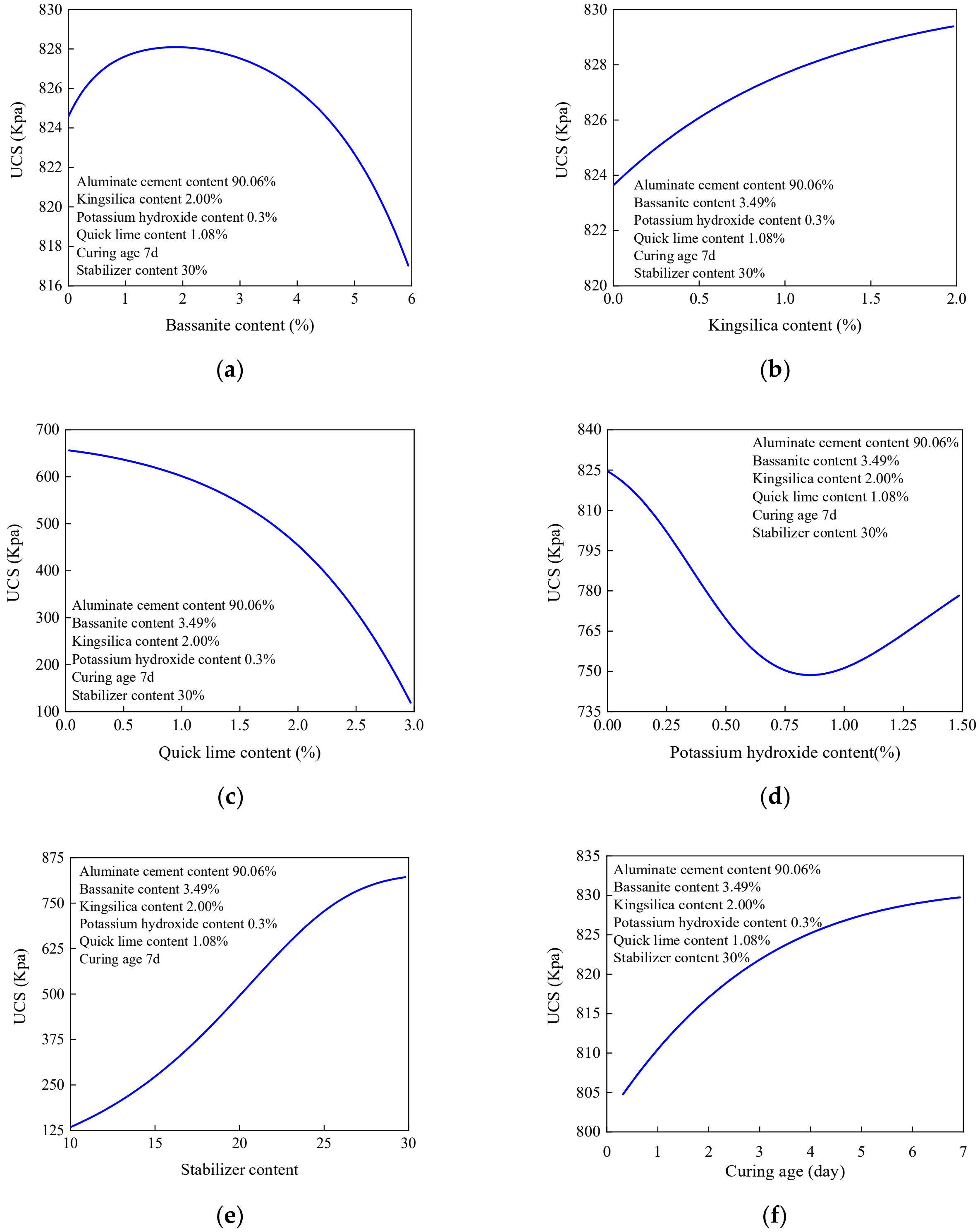

Figure 13. Influence of various influencing factors on unconfined compressive strength. (**a**) Influence of bassanite content on unconfined compressive strength. (**b**) Influence of kingsilica content on unconfined compressive strength. (**c**) Influence of quick lime content on unconfined compressive strength. (**d**) Influence of potassium hydroxide content on unconfined compressive strength. (**e**) Influence of stabilizer content on unconfined compressive strength. (**f**) Influence of curing age on unconfined compressive strength.

It can be observed from Figure 13b that the UCS of treated marine clay will increase with increasing content of kingsilica. It shows that the unconfined compressive strength of the stabilized soil can be improved by adding kingsilica when other influencing factors are determined. Kingsilica can react with CH in cement hydration products to form CSH gel. This reduces the content of CH to a certain extent and improves the degree of cement paste. CSH gel can also continuously fill the pores between cement particles, reduce the water–cement ratio, and thus improve the strength of cured soil.

As observed from Figure 13c, in the current analysis of the optimization results, UCS decreases with the increase in quick lime content when other influencing factors are determined by optimization analysis. It shows that the curing effect of the stabilizer will be counteracted by adding lime in this case. The main functions of lime addition in marine clay are ion exchange, pozzolanic reaction, and carbonation. However, when the amount of lime is large, there is not enough active aluminum oxide and silica in the clay to react with lime chemically, which results in relatively fewer stable minerals in the treated marine clay, thus reducing the strength of the chemically treated marine clay [30].

It can be seen from Figure 13d,e,f that the addition of potassium hydroxide will make the UCS decrease first and then increase, and there is a minimum value for UCS. When the content of potassium hydroxide increases to about 0.8%, the UCS decreases to the lowest strength, 750 kPa. It will then increase with the addition of potassium hydroxide. The dosage of stabilizer and curing age all promote UCS, and there is a positive correlation between UCS, stabilizer dosage, and curing age. It is not difficult to find that the more stabilizer is added, the harder the marine clay will be, and the longer the treated clay is cured, the stronger it will be.

4. Conclusions

This study conducts comprehensive experiments and ANN-based modeling for analyzing the effects of stabilizer type, curing age, and content on the compressive strength of marine clay of the Qingdao region of China. A series of unconfined compressive strength tests, that were designed based on an orthogonal approach, was conducted first, followed by the development of ANN-based modeling. Further, optimization and sensitivity analyses were conducted to explore the influence of different parameters on the compressive strength of treated marine clay. The following conclusions can be drawn based on the study:

1. Through the unconfined compressive strength test and range analysis, it can be found that there is a complex non-linear relationship between the influencing factors and the unconfined compressive strength under different stabilizer dosages and curing ages. The increment of stabilizer content from 10% to 30% shows a substantial increment in the unconfined compressive strength of the admixed soil after a 28 d curing period when the aluminate cement content is 89.5%, in which the primary and secondary order of influence on the unconfined compressive strength is potassium hydroxide > kingsilica > quick lime > bassanite.
2. By analyzing the stress–strain behavior of soil samples, it is found that the strength increases continuously with an increase in stabilizer content and the extension of curing age, showing a trend of transition from plasticity to brittleness.
3. The forecasting model is established using an artificial neural network (ANN), which verifies the validity and high performance of the model. It is proved that ANN-based modeling can be used as a tool to analyze complex non-linear relationship problems under multiple factors.
4. Sensitivity analysis results based on the ANN model show that the unconfined compressive strength (UCS) is most sensitive to the change in quick lime content. The influence of quick lime should be given priority in the formulation design of stabilizers. The results are in agreement with the range analysis. It further proves that the artificial neural network has high performance and good forecasting ability.
5. The results of optimization analysis based on the ANN model show that the maximum UCS can reach about 830 kPa. When the maximum UCS is reached, the model fits the values of various factors, similar to the results of the unconfined compressive strength tests, and the curing scheme can be optimized according to the results of the model.

6. The influence of various influencing factors on the unconfined compressive strength of solidified soil can be optimized using the ANN model, and the influence trend of a single variable on UCS can be obtained. The results show that there is a critical value for the influence of the amount of bassanite and potassium hydroxide, which can be used for further optimize the design of stabilizer components.

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