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Prediction Model of Compressive Strength Development in Concrete Containing Four Kinds of Gelled Materials with the Artificial Intelligence Method

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Featured Application: Predict the concrete compressive strength development over time.

Abstract: Green concrete has been widely used in recent years because its production compliments environmental conservation. The prediction of the compressive strength of concrete using non-destructive techniques is of interest to engineers worldwide. Such methods are easy to carry out because they require little or no sample preparation. Conventional models and artificial intelligence models are two main types of models to predict the compressive strength of concrete. Artificial intelligence models main include the artificial neural network (ANN) model, back propagation (BP) neural network model, fuzzy model etc. Since both conventional models and artificial intelligence models are flawed. This study proposes to build a concrete compressive strength development over time (CCSDOT) model by using conventional method combined with the artificial intelligence method. The CCSDOT model performed well in predicting and fitting the compressive strength development in green concrete containing cement, slag, fly ash, and limestone flour. It is concluded that the CCSDOT model is stable through the use of sensitivity analysis. To evaluate the precision of this model, the prediction results of the proposed model were compared to that of the model based on the BP neural network. The results verify that the recommended model enjoys better flexibility, capability, and accuracy in predicting the compressive strength development in concrete than the other models.

Keywords: compressive strength; prediction; model; gelled materials

1. Introduction

Concrete is defined as a composite mixture of cement, aggregate, water, and when necessary chemical and mineral admixtures, and it is one of the most important materials in the construction industry. Concrete can be placed into moulds of various shapes and sizes, and then hardened under certain conditions [1–3]. Green concrete is one kind of the various concretes which has been used widely recently. People pay much attention to the performance of concrete. The compressive strength of concrete is assumed to be one of the most important and essential properties of concrete since it usually shows the overall quality of concrete [4].

In the last few decades, chemical and mineral admixtures, such as fly ash, slag, and limestone flour, were gradually added into concrete, and such forms of concrete were used in large civil engineering and hydraulic projects. In recent years, the utilization of mineral admixtures in concrete has shown a dramatic increase due to its economic, environmental, and technical benefits. Using mineral admixtures to replace partial cement is an effective way to reduce environmental pollution [5–10]. Besides, this strategy shows the potential to lower concrete production cost, conserve energy and resources, and also reduce waste [5–10]. Moreover, mineral admixtures offer several technical benefits to concrete, such as improving durability [5,8–11], workability [9,11,12] and permeability [7,9], reducing hydration evolution heat [9,12], and frequently improving compressive strength [7,9,13–16].

There are two main types of models to predict the compressive strength of concrete mixed with mineral admixtures. First, there are conventional models. Next, there are artificial intelligence models. Conventional models are based on statistical analysis, and many have built-in linear and nonlinear regression equations. Thus, they have the advantages of generating easy-to-use regression constants and in estimating the significance of the various input variables. Nikoo, M. et al. [17] used multiple linear regression to predict compressive strength of nine laboratory concrete specimens. Ahmed, M.S. [18] built a statistical model to predict the compressive strength of concrete containing different matrix mixtures at fixed age.

However, conventional models were developed with a fixed equation with a limited amount of data and parameters. If new data is different from the original data, then it is necessary to update not only the coefficients in the model but also the form of its equation. Artificial intelligence models were more adaptable when compared to conventional models. Khosravani, M.R. et al. [19] implemented an artificial intelligence (AI) system to predict dynamic mechanical properties, such as compressive strength, elastic modulus and tensile strength, of ultra-high performance concrete. The system was developed with the framework of case-based reasoning methodology, which was a learning methodology that utilized similar previous cases to solve particular new problems, as a problem-solving AI method. Bui, D.K. et al. [20] developed an expert system based on the artificial neural network (ANN) model in association with a modified firefly algorithm (MFA). And the proposed approach could provide an efficient and accurate tool to predict and design high-performance concrete. Sadowski, L. et al. [21] adopted the artificial neural networks (ANNs) to predict the compressive strength of low-strength concrete screeds modified using high volume of mineral dusts sourced from industrial wastes based on the composition of the concrete and ultrasonic pulse velocity. Trtnik, G. et al. [22] predicted the compressive strength of concrete by using an artificial neural network and ultrasonic pulse velocity. The results were satisfactory. Yeh, I.C. [23] adopted artificial neural networks (ANN) to predict the compressive strength of high-performance concrete, concluding that the ANN model was more accurate than a model based on regression analysis and it was easy to use ANN models for numerical experiments to review the effects of the proportions of each variable on the concrete mix. Kasperkiewics, J. [24], Lai, S. [25] and Lee, S.C. [26] also applied the neural network for predicting the properties of conventional concrete and high-performance concretes. Ni, H.G. [27] proposed a method to predict the 28-day compressive strength of concrete by using multilayer feed-forward neural networks. Demir, F. [28] developed a fuzzy model to predict normal and high-strength concrete. And the main advantage of the fuzzy model was its ability to describe knowledge in a descriptive human-like manner in the form of simple rules using linguistic variables only [29]. Hwang, K. [30] derived an equation from experimental results to estimate the compressive strength development in concrete which contained fly ash. Bilim, C. [31] applied an artificial neural network to predict the compressive strength of ground granulated blast furnace slag concrete by using concrete ingredients as input parameters. Khademi, F. et al. [4] used two different data-driven models, multiple linear regression and artificial neural network, in a MATLAB software environment to estimate the compressive strength of concrete. However, artificial intelligence models require a large training data set due to its "black-box" techniques [32].

Although there is a lot of literature about predicting the compressive strength of concrete, only a few of researchers could express the long-term compressive strength development in a certain kind of concrete. Meanwhile, the measurement and prediction of the compressive strength of concrete using non-destructive techniques is of interest to engineers worldwide. Such methods are easy to carry out because they require little or no sample preparation. Unlike artificial intelligence models that use "black-box" techniques and need a lot of data, the concrete compressive strength development over time (CCSDOT) model proposed in this study generates explicit formulas, which provide important advantages in practical applications. Meanwhile, adding optimization algorithms makes this model more adaptable to new data than conventional models. Moreover, the model can predict the compressive strength development over time in concrete which incorporated with up to three kinds of mineral admixtures by using concrete mix proportions.

Since the existing research can either only predict the compressive strength of a certain concrete or predict the compressive strength of concrete at a certain age, it is necessary to carry out the research about a model to predict the compressive strength of all kinds of concrete development over time. The main objective of this research is to construct a CCSDOT model to predict the compressive strength development over time of all kinds of concretes. These concretes are incorporated with different mineral admixtures. The model requires a few trial tests, the concrete's ingredients, and the concrete's age. For this purpose, a computer program of sequence quadratic programming was developed in FORTRAN. Furthermore, the results obtained from the CCSDOT model were compared with the results of the experiments and backpropagation (BP) neural network. By adopting this predicting model, considerable costs and time could be saved.

The outline of the rest of the study is as follows: Section 2 describes the model derivation and discusses the sequential quadratic programming method. Applications in green concrete are presented in Section 3, including the cross-validation and fitting analysis. In Section 4, the sensitivity analysis is presented, and the optimal performance of the model is compared with the optimal performance of the BP neural network. Section 5 is the conclusions of this study.

2. Model and Methodology

2.1. Concrete Compressive Strength Development over Time Model

A lot of researchers have introduced a relationship between the concrete compressive strength and curing time with different logarithmic equations [23,33–35]. Yeh, I.C. [23] adopted the following equation to predict the compressive strength of high-performance concrete, and then the results were compared to the results by ANN:

$$f_c'(t) = AY^B \cdot [C \ln(t) + D]. \tag{1}$$

where $f_c'(t)$ is the compressive strength of high-performance concrete at t days, t is age at test, Y is water-to-binder ratio and A, B, C, and D are regression coefficients.

However, in practical concrete engineering, the strength evaluation of concrete is generally based on the strength of curing after 28 days. Many concrete properties have a great relationship with the strength after 28 days [36]. Besides, there are many factors affecting the 28-day compressive strength of concrete. Therefore, the model in this study is built based upon the 28-day compressive strength of concrete and the modified logarithmic relationship established in the literatures. Moreover, in order to reflect the characteristics of different kinds of concrete, the parameter λ is introduced to the model.

The concrete compressive strength development over time model is written as:

$$S_t = S_{28}(1 + \lambda \ln \frac{t}{28}). \tag{2}$$

where S_{28} is the concrete compressive strength after t days. Also, λ expresses the factor of the concrete compressive strength in a later period.

As the development of concrete progressed, more and more kinds of gelled materials were used in concrete. In summary, there are four main kinds of gelled materials: cement, slag, fly ash and limestone flour. Also, the gelled materials greatly influence the compressive strength of concrete [36]. In general, the use of slag and fly ash is unfavorable to the early age compressive strength development of concrete compared to cement while it is beneficial to the long-term compressive strength development of concrete compared to cement. Thus it is reasonable that the 28-day compressive strength (S_{28}) is dictated by the contribution of cement, slag, fly ash and limestone flour.

$$S_{28} = S_{28C} + S_{28SL} + S_{28FA} + S_{28LF}. \tag{3}$$

where S_{28C} is the 28-day concrete compressive strength contribution of cement, S_{28SL} is the 28-day concrete compressive strength contribution of slag, S_{28FA} is 28-day concrete compressive strength contribution of fly ash and S_{28LF} is 28-day concrete compressive strength contribution of limestone flour.

A positive linear correlation between the content and the 28-day compressive strength contribution of each gelled material means that the impact index of gelled material x (i_x) is equal to 1, x can be cement, slag, fly ash or limestone flour.

$$S_{28x} = S_x q_x. \tag{4}$$

where S_{28x} is the 28-day concrete compressive strength contribution of gelled material x, S_x is the 28-day compressive strength of gelled material x, q_x is the percentage content by weight of gelled material x. Substitute Equation (4) into Equation (3) and we get Equation (5). The 28-day compressive strength of concrete (S_{28}) is derived as follows:

$$S_{28} = S_C q_C + S_{SL} q_{SL} + S_{FA} q_{FA} + S_{LF} q_{LF}. \tag{5}$$

where S_C is the 28-day compressive strength of cement, S_{SL} is the 28-day compressive strength of slag, S_{FA} is the 28-day compressive strength of fly ash and S_{LF} is 28-day compressive strength of limestone flour. q_C, q_{SL}, q_{FA}, and q_{LF} are the percentage of each gelled material content which can be expressed as follows:

$$q_x = \frac{m_x}{m_C + m_{SL} + m_{FA} + m_{LF}} \times 100\%. \tag{6}$$

where m_x is the quantity of gelled material. In addition, m_C is the quantity of cement used in concrete, m_{SL} is the quantity of slag used in concrete, m_{FA} is the quantity of fly ash used in concrete, and m_{LF} is the quantity of limestone flour used in concrete.

However, the correlation between the content and the 28-day compressive strength contribution of each gelled material is always nonlinear in practical engineering applications, so parameter i_x is introduced into the model. For instance, the 28-day compressive strength of concrete increases rapidly with increases in the cement content at first. However, when the content of cement reaches a certain level, the 28-day compressive strength of concrete increases slowly with an increase in the amount of cement. In such cases, the impact index of cement is greater than 0 and less than 1. The 28-day compressive strength of concrete increased slowly with increases in the fly ash content at first. However, when the content of fly ash reaches a certain level, the 28-day compressive strength of concrete increases quickly. In this case, the impact index of fly ash is always greater than 1. In order to measure the contribution of different gelled materials to the 28-day compressive strength of concrete, the 28-day compressive strength contribution coefficient of gelled material x is introduced into the model.

$$S_{28x} = S_x {q_x}^{i_x}. \tag{7}$$

where i_x is the impact index of gelled material x. In order to compare the influence of each kind of gelled material on concrete, S_x is normalized as follows:

$$ss_x = S_x / S_C \tag{8}$$

where ss_x is the 28-day compressive strength contribution coefficient of gelled material x. Substitute Equation (7) into (3) and we get Equation (9).

$$S_{28} = S_C {q_C}^{i_C} + S_{SL} {q_{SL}}^{i_{SL}} + S_{FA} {q_{FA}}^{i_{FA}} + S_{LF} {q_{LF}}^{i_{LF}}. \tag{9}$$

where i_C is the impact index of cement, i_{SL} is the impact index of slag, i_{FA} is the impact index of fly ash and i_{LF} is the impact index of limestone flour.

Just like the 28-day compressive strength of concrete, the factor of compressive strength in later periods is expressed as the sum of the contribution of each kind of gelled material.

$$\lambda = \lambda_C {q_C}^{i_C} + \lambda_{SL} {q_{SL}}^{i_{SL}} + \lambda_{FA} {q_{FA}}^{i_{FA}} + \lambda_{LF} {q_{LF}}^{i_{LF}}. \tag{10}$$

where λ_C is the factor of compressive strength in the later period of cement, λ_{SL} is the factor of the compressive strength in later periods of slag, λ_{FA} is the factor of the compressive strength in later periods of fly ash and λ_{LF} is the factor of the compressive strength in later periods of limestone flour.

By using the compressive strength test results of concrete with various proportions of the same aggregates and gelled materials, the 12 parameters (S_C, S_{SL}, S_{FA}, S_{LF}, i_C, i_{SL}, i_{FA}, i_{LF}, λ_C, λ_{SL}, λ_{FA}, λ_{LF}) of the model are inverted based on the optimization algorithm.

2.2. Methodology

To find the 12 parameters in the model is a nonlinear constrained optimization problem. There are several common optimization methods including the penalty function method, augmented multiplier method, and the sequence quadratic programming (SQP) method. SQP has a wide range of applications and good development. When compared with other optimization algorithms, its most prominent advantages are good convergence, high computational efficiency, and strong edge search ability. Therefore, this research chooses the SQP method to find the 12 parameters.

A typical constrained nonlinear programming problem can be expressed as:

$$\begin{array}{ll} \min f(X) & \\ s.t. & \begin{array}{ll} h_i(X) = 0 & i = 1, 2, \cdots, m \\ g_j(X) \geq 0 & j = 1, 2, \cdots, n \end{array} \end{array}. \tag{11}$$

where the objective function $f(X)$, equality constraint $h_i(X)$ and inequality constraint $g_i(X)$ are all second order, continuous and differentiable. The Lagrange function of this problem is given in Equation (12).

$$L(X, \gamma) = f(X) + \sum_{i=1}^{m} \gamma_i h_i(X) + \sum_{j=m+1}^{n} \gamma_j g_j(X). \tag{12}$$

where γ_i and γ_j are Lagrange operators.

According to the idea of SQP, this problem can be transformed into a series of quadratic programming (QP) problems. The QP problem of X_{k+1} can be further changed into the QP problem of search direction d in order to ensure that X_k is close to the feasible solution in each iteration and the objective function also has a downward trend. Then, the following form of the QP subproblem can be obtained:

$$\begin{array}{ll} \min\limits_{d \in R^n} & \frac{1}{2} d^T H_k d + (\nabla f(X_k))^T d \\ s.t. & \begin{array}{l} (\nabla h_i(X))^T d + h_i(X) = 0 \\ (\nabla g_j(X))^T d + g_j(X) = 0 \end{array} \end{array}. \tag{13}$$

$$X_{k+1} = X_k + \alpha_k d_k. \tag{14}$$

where α_k is the step size. The iterative process of the SQP method can be expressed as follows:

Step 1: Determine the initial value of X^0 and H^0.

Step 2: Solve the QP subproblem and determine the search direction d^k and $\gamma_{i,j}^{k+1}$.

Step 3: $X_{k+1} = X_k + \alpha_k d_k$, if the convergence condition is satisfied, (X_{k+1}, γ^{k+1}) is taken as the optimal solution of the original problem; if not, return to Step 2 and continue to iterate.

The problem in this study has variable constraint conditions and objective function. Also, the problem is not suitable for iteration with traditional Lagrange operators. This study adopts intelligent method, the monitoring technology combining constraint condition and objective function, to select new iteration points. In addition, the possibility of failure in optimization iteration is dealt with by temporary expansion of the feasible domain method. These changes improve the effectiveness and computational efficiency of the optimization algorithm. In consequence, the overview of the model and methodology is shown in Figure 1.

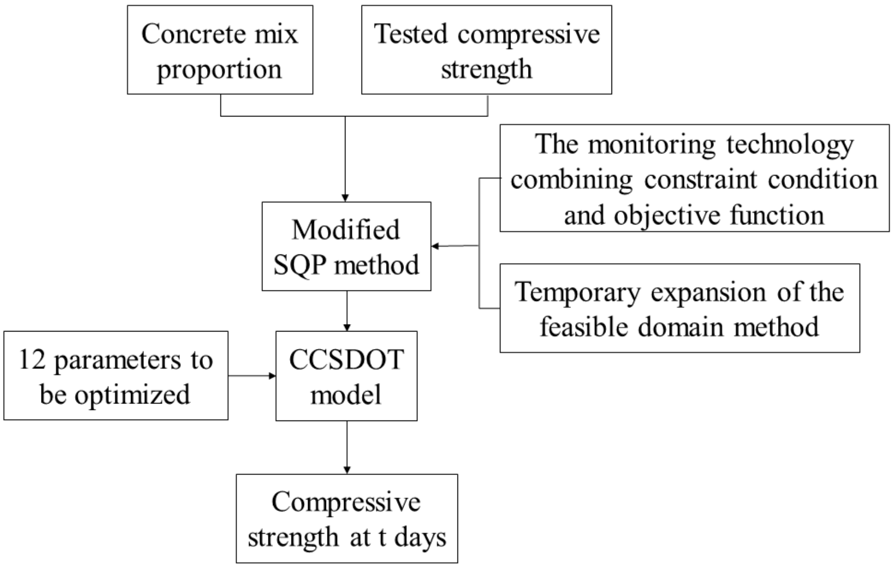


Figure 1. Overview of the model and methodology. SQP: quadratic programming; CCSDOT: concrete compressive strength development over time.

3. Application in Green Concrete

In this study, the 1st to 11th groups of the 66 concrete compressive strength mix proportions and tests results from XU, G.Q. [37] were adopted. Table 1 is the mix proportions of the green concrete and Table 2 is the tested results.

Table 1. Mix properties of green concrete.

Group	Cement/(kg/m^3)	Limestone Flag/(kg/m^3)	Fly Ash/(kg/m^3)	Sand/(kg/m^3)	Gravel/(kg/m^3)	Water/(kg/m^3)	Water Reducer/(kg/m^3)
1	252	54.0	54.0	828	1053	158.4	9.00
2	252	64.8	43.2	828	1053	158.4	9.00
3	252	75.6	32.4	828	1053	158.4	9.00
4	252	86.4	21.6	828	1053	158.4	9.00
5	252	97.2	10.8	828	1053	158.4	9.00
6	252	108.0	0	828	1053	158.4	9.00
7	216	72.0	72.0	828	1053	158.4	9.00
8	216	86.4	57.6	828	1053	158.4	9.00
9	216	100.8	43.2	828	1053	158.4	9.00
10	216	115.2	28.8	828	1053	158.4	9.00
11	216	129.6	14.4	828	1053	158.4	9.00

Table 2. Tested compressive strength of green concrete.

Group	Compressive Strength/MPa		
	3 d	7 d	28 d
1	17.6	23.4	34.0
2	17.0	22.6	33.3
3	17.0	25.0	34.6

Table 2. *Cont.*

Group	Compressive Strength/MPa		
	3 d	7 d	28 d
4	18.8	23.7	33.6
5	18.3	23.8	33.4
6	16.9	22.0	30.3
7	13.7	18.9	28.0
8	14.1	19.4	30.2
9	15.2	20.3	30.6
10	13.9	17.4	28.0
11	14.6	19.2	28.6

3.1. Model Cross-Validation

One group of 11 tests results was chosen randomly as a testing set and the rest of the ten groups were selected as training sets automatically. In Figure 2, the dense bars represent the tested compressive strength and the sparse bars represent the predicted compressive strength. Comparisons of the tested data and predicted data in each group are given in Figure 2, graphically. This revealed that the model can predict concrete compressive strength over time precisely.

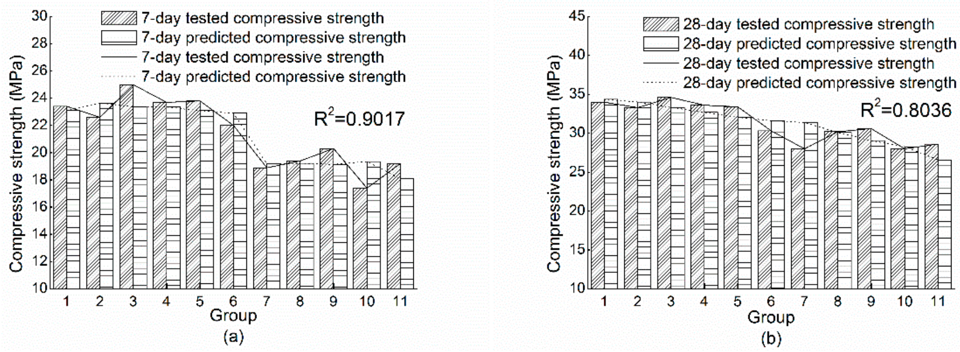


Figure 2. Comparison of tested and predicted compressive strength of concrete at the age of (**a**) 7 days and (**b**) 28 days.

With regard to the prediction accuracy, the error analysis, including the relative error analysis and the absolute value of the relative error analysis, of both the 7-day and 28-day compressive strength were done. The average of the absolute value of the relative error of the 7-day compressive strength is 4.18% while it is 3.96% for the 28-day compressive strength. And correlation coefficient (R^2) for 7-day compressive strength reaches 0.9017 while R^2 for 28-day compressive strength is 0.8036. These values are acceptable in practical engineering.

3.2. Fitting Analysis

The performance of the fitted compressive strength and tested compressive strength of the 11 samples using the model mentioned earlier can be seen in Figures 3 and 4. In Figure 3, the hollow circles represent the 7-day compressive strength of the tested value and fitted value. Pentagrams denote the 28-day compressive strength of the tested value and fitted value. The black solid line represents the fitted value and tested value are exactly same. Black-dashed lines show the upper and lower fitted bounds at a 5% deviation level and the result in Figure 2 indicates the model performs reasonably well.

Figure 4 shows a comparison of the fitted and tested compressive strength of concrete at an age of 7 days and 28 days, respectively. Hollow triangles represent the 7-day tested compressive strength while the hollow circles express the 28-day tested compressive strength. Meanwhile, black solid triangles express the 7-day fitted compressive strength while black solid circles represent the

28-day fitted compressive strength. Graphically, the figure illustrates that the model can fit both the 7-day compressive strength and 28-day compressive strength very well, with R^2 for 7-day compressive strength range from 0.9285 to 0.9506 while R^2 for 28-day compressive strength range from 0.8138 to 0.8606 as shown in Table 3.

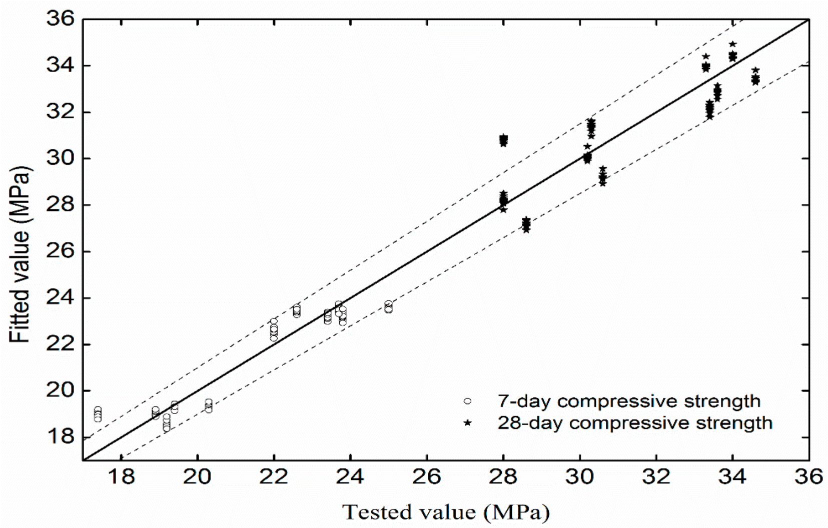


Figure 3. Relationship between tested compressive strength and fitted compressive strength of concrete.

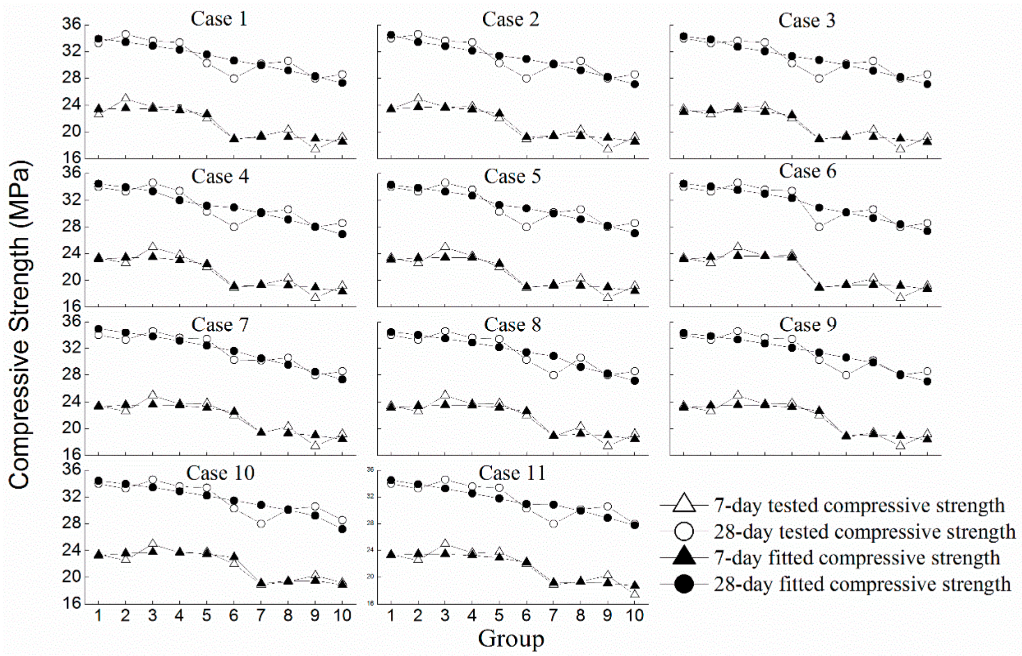


Figure 4. Comparison of tested and fitted compressive strength of concrete at age of 7 days and 28 days.

Figure 5 is a box-plot of the absolute value of the relative error between the tested and fitted compressive strength from 10 of the 11 groups randomly. The figure indicates that the average of the absolute value of the relative error of each group is lower than 4% and that the average of all of the 11 groups' absolute value of relative error is 3.31%. This average indicates that the model mentioned earlier performs well in fitted compressive strength. Moreover, it reveals that the error distribution is stable, thus proving the model has great applicability.

Table 3. The R^2 between tested and fitted compressive strength of concrete at age of 7 days and 28 days.

Group	R^2	
	7 d	**28 d**
1	0.9311	0.8470
2	0.9311	0.8236
3	0.9382	0.8406
4	0.9293	0.8374
5	0.9313	0.8606
6	0.9431	0.8494
7	0.9285	0.8247
8	0.9312	0.8138
9	0.9456	0.8252
10	0.9506	0.8161
11	0.9395	0.8600

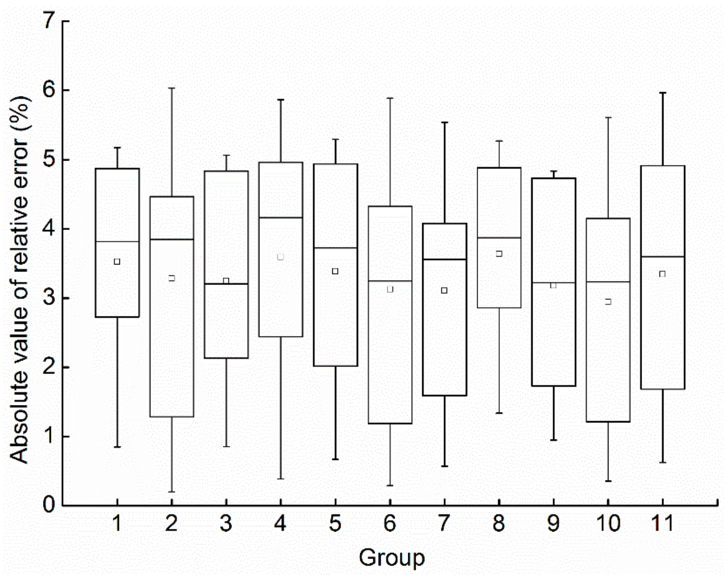


Figure 5. The Box-plot shows the absolute value of the relative error between the tested and fitted compressive strength from 10 of 11 groups randomly.

4. Discussion

4.1. Sensitivity Analysis

People may pay more attention to the compressive strength of concrete and design the optimal mix proportions with a few trial test before they determine the final mix proportions. Meanwhile, it is important to decide the proper number of groups for each similar mix proportion trial test. For a laboratory test, a proper number of groups can economize the time and cost.

Sensitivity analysis is a method to quickly find the proper number of groups of each similar mix proportion trial test. In Figure 6, at the very beginning, the absolute value of relative error decreases sharply as we increase the number of training sets. Then, as the number of training sets rises, the absolute value of relative error gradually becomes steady, and eventually the error goes below 5%. Meanwhile, the degree of dispersion of the absolute value of the relative error decreases as the number of training sets rises.

Figures 7 and 8 show the relative error sensitivity analysis and the absolute value of the relative error sensitivity analysis between the predicted data and tested data. They show similar characteristics to each other in Figure 6. It is not difficult to understand that the accuracy of prediction increases as training sets increase. When training sets reach 4 groups, either the relative error or the absolute value of the relative error between predicted and tested 7-day and 28-day compressive strength of group 6 is smaller than 5%. Even the average absolute value of the relative error is also smaller than 5%. It is acceptable in practical engineering. Therefore, in order to meet the economic and technical demands, it is suitable to choose at least 4 training sets in this model.

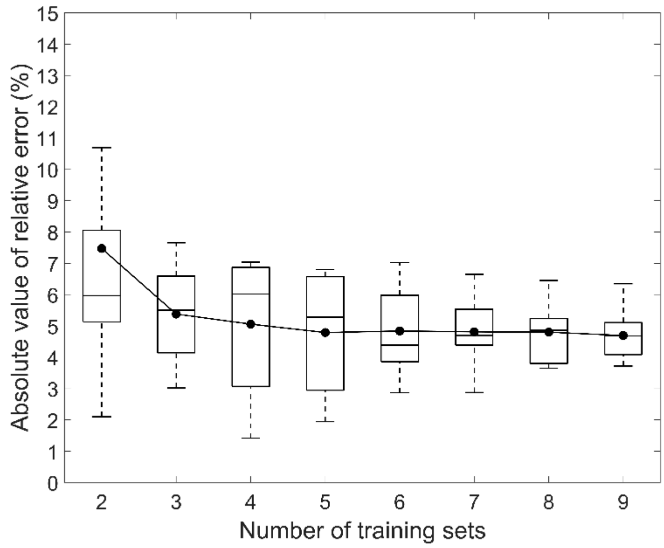
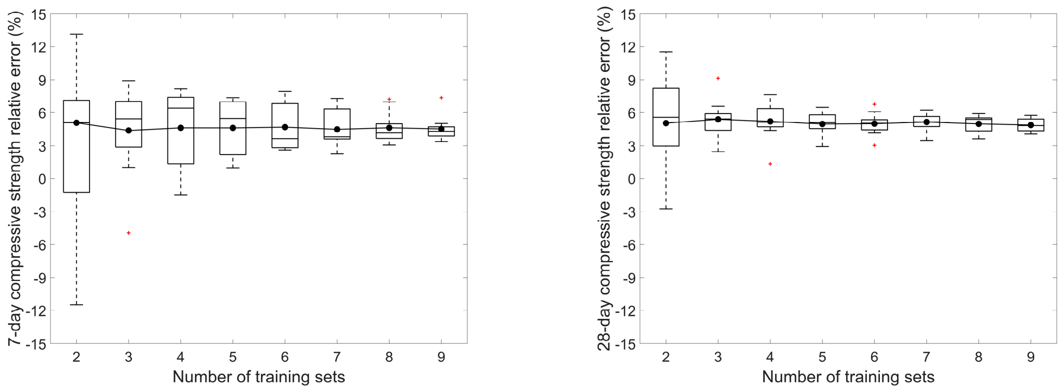
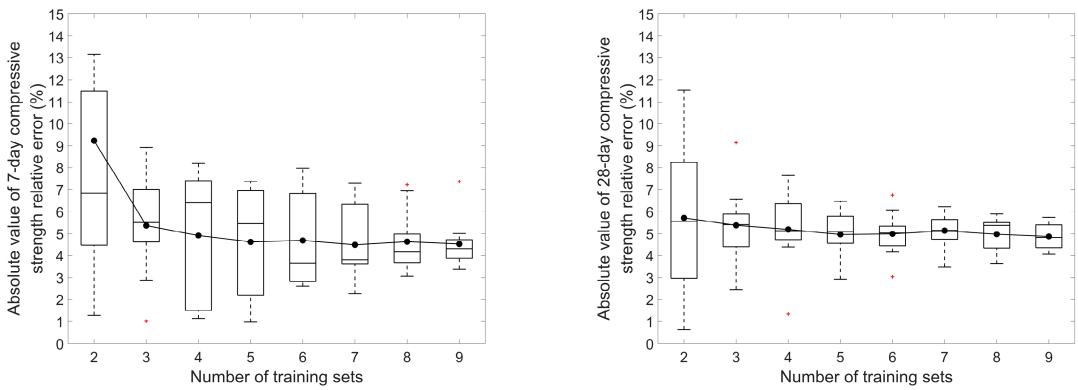


Figure 6. Sensitivity analysis between the number of training sets, and the average absolute value of the relative error between predicted and tested the compressive strength of group 6.



(**a**) (**b**)

Figure 7. Sensitivity analysis between the number of training sets, and relative error between predicted and tested (**a**) 7-day and (**b**) 28-day compressive strength of group 6.



(**a**) (**b**)

Figure 8. Sensitivity analysis between the number of training sets, and the absolute value of the relative error between predicted and tested (**a**) 7-day and (**b**) 28-day compressive strength of group 6.

4.2. Comparison to BP Neural Network

Table 4 shows the tested compressive strength results from XU, G.Q. [37], predicted compressive strength by BP neural network model and predicted compressive strength by the CCSDOT model. The BP neural network model used 61 groups of data and the CCSDOT model only used 10 groups of data.

Table 4. Compressive strength of green concrete containing fly ash and limestone flour. BP: back propagation.

Group	Compressive Strength (MPa)								
	Tested			BP Neural Network			CCSDOT Model		
	3 d	7 d	28 d	3 d	7 d	28 d	3 d	7 d	28 d
6	16.9	22.0	30.3	16.99	21.36	31.07	16.94	22.26	30.96

We put the proportions of the 10 groups of concrete and the measured compressive strength at each age of group 6 into the model, then the 12 parameters can be calculated as shown in Table 5.

Table 5. Optimal parameters of CCSDOT model.

Parameter	Value (MPa)	Parameter	Value	Parameter	Value
S_C	43.03	i_C	0.4742	λ_C	0.1585
S_{SL}	0	i_{SL}	0	λ_{SL}	0
S_{FA}	−0.68	i_{FA}	1.3229	λ_{FA}	0.9454
S_{LF}	−37.00	i_{LF}	1.6029	λ_{LF}	0.4746

Substitute the results in Table 5 into Equation (8) and we get ss_x as listed in Table 6

Table 6. 28-day compressive strength contribution coefficient of each gelled material.

Parameter	Value
ss_C	1
ss_{SL}	0
ss_{FA}	−0.0158
ss_{LF}	−0.8599

In practical engineering, the use of fly ash and limestone flour is unfavorable to the early age compressive strength development of concrete compared to cement. Thus, ss_{FA} and S_{28LF} are less than 0. And limestone flour is more unfavorable to the early age compressive strength development of concrete compared to fly ash, which is conformed to reality. And the use of fly ash and limestone flour is beneficial to the long-term compressive strength development of concrete compared to cement. Therefore, λ_{FA} and λ_{LF} are greater than λ_C. Furthermore, S_3 and S_7 can be calculated based on Table 5 and Equation (2).

Table 7 shows the relative error of the predicted results by the BP neural network and CCSDOT model. The performance of CCSDOT is better than BP at any age of concrete. The CCSDOT model is more accurate when compared to the BP neural network model.

Table 7. Comparison between the predicted results of BP neural network and CCSDOT model.

Model	Relative Error (%)		
	3 d	7 d	28 d
BP	0.532	−2.909	2.541
CCSDOT	0.237	1.182	2.178

5. Conclusions

(1) This research developed a CCSDOT model to predict the compressive strength development in concrete that incorporated with several kinds of gelled materials. The CCSDOT model combined the advantages of conventional models and artificial intelligence models. Modified SQP method was adopted to solve the nonlinear constrained optimization problem.
(2) The CCSDOT model performed well in predicting and fitting the compressive strength development in green concrete containing cement, slag, fly ash, and limestone flour. The error analysis proved the model has great applicability.
(3) It is concluded that the CCSDOT model is stable and is very applicable through the use of sensitivity analysis. In practical applications, it is suitable to choose at least 4 training sets in this model to meet the economic and technical demands.
(4) Compared to the BP neural network, the CCSDOT model is more accurate.

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