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Machine learning-based prediction of residual compressive strength of UHPC after high-temperature damage

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Abstract
By using 11 influencing factors of water-cement ratio, silica-cement ratio, fly ash-cement ratio, sand-cement ratio, quartz powder-cement ratio, steel fiber admixture, PP fiber admixture , room temperature standard curing, hot water curing, dry heat curing and heating temperature as input variables, a BP neural network, Sparrow Search Algorithm Optimized Artificial Neural Network (SSA-BP) , Genetic Algorithm Optimized Artificial Neural Network (GA-BP) , and Support Vector Machine Regression (SVR) four models were established to predict the residual compressive strength of ultra-high performance concrete (UHPC) after high temperature damage. The results show that all four machine learning models can predict the residual compressive strength of UHPC after high temperature damage with high accuracy compared with the prediction results of existing empirical calculation models, and the error is basically controlled within 15%. The prediction results of the GA-BP model is the best, and its R2 reaches 0.949.

Keywords: *Ultra-high performance concrete; Residual compressive strength; High temperature damage; Machine learning.*

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I. INTRODUCTION

With the acceleration of industrialization and urbanization, the causes of fire are becoming more and more complex, and the frequency of fire and the loss of life and property caused by fire are showing a rapid growth trend [1], and fire has become one of the main risks that threaten the safety of concrete structures [2]. The high temperatures generated by fires can lead to cement paste dehydration, aggregate decomposition, loss of concrete quality, deformation, loss of strength, and bursting of concrete [3-6]. How to assess the residual bearing capacity of damaged concrete structures after high temperature and adopt effective repair measures is an urgent problem.

The prediction method of concrete compressive strength is mainly divided into two categories: (ⅰ) empirical formula method, according to the test results to summarize the influencing factors of compressive strength and its role in the law, the establishment of the compressive strength model, and then deduce the formula for calculating the compressive strength of concrete [7-10]; (ⅱ) machine learning algorithms, the formation of the prediction model of the compressive strength of concrete through the computer [11-13].

There are numerous factors affecting the compressive strength of UHPC [14-19]. The existing empirical calculation models of compressive strength after high-temperature damage are all obtained based on the respective test data regression fitting and other methods, which have limited applicability under the role of multi-factors, whereas the machine learning method is able to establish a nonlinear multi-mapping analysis under the role of multi-factors to discover the relationship between each raw material component of UHPC and its residual compressive strength after high-temperature damage, and more accurate results can be obtained with a small number of tests.

In this paper, using the 214 sets of UHPC residual compressive strength test data after high-temperature damage collected in the previous period, with the help of Matlab software, we establish BP neural network, BP neural network optimized by Sparrow Search Algorithm (hereinafter referred to as SSA), BP neural network optimized by Genetic Algorithm (hereinafter referred to as GA), and Support Vector Machine Regression (hereinafter referred to as SVR) with four kinds of models to predict the residual compressive strength of UHPC after high-temperature damage and compare the prediction results of machine learning models with those based on test experience. (hereinafter referred to as SVR), and support vector machine regression (hereinafter referred to as SVR) four models to predict the residual compressive strength of UHPC after high-temperature damage, and to compare the prediction results of the machine learning model with those of the model based on the experimental empirical calculations, with a view to providing a reference for the effective application of the machine learning method to the prediction of compressive strength after high-temperature damage of UHPC.

II. DATA SOURCES AND PROCESSING

Based on the experience, 11 parameters such as water-cement ratio, silica fume/cement, fly ash/cement, quartz sand/cement, quartz powder/cement, steel fiber dosage, PP fiber dosage, curing method, and heating temperature are hypothesized to have a strong influence on the residual compressive strength of UHPC after high temperature damage. For this purpose, experimental data from national and international literature [3, 9, 14-17, 20-24] were collected to form 214 sample data sets.

Due to the large number of variables entered into the established prediction model, in order to verify the reliability of the sample data, it is necessary to carry out a multicollinearity test between the input variables to eliminate the factors with too high correlation [25]. In this paper, the Spearman correlation coefficient method is used for the test. It is generally believed that when the absolute value of the correlation coefficient of two input variables is ≥0.8, there is a certain covariance between the two variables. The correlation coefficients of all input variables were calculated and plotted in a heat map, as shown in Figure 1. In the graph, W/B is water-binder ratio, SF/C is silica fume/cement, FA/C is fly ash/cement, S/C is quartz sand/cement, Qu/C is quartz powder/cement, S-F is steel fiber dosage, PP-F is PP fiber dosage, NW is ambient conditioning, HW is hot-water conditioning, DA is dry-heat conditioning, and T is temperature.

As can be seen in Figure 1, the correlation coefficient between standard maintenance NW and hot water maintenance HW is 0.94, but since the maintenance method is a mandatory option for consideration, it is not censored, and the correlation results between the rest of the input variables are in line with the modeling requirements.

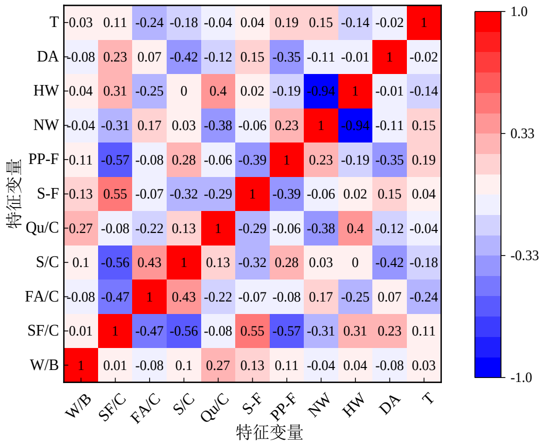


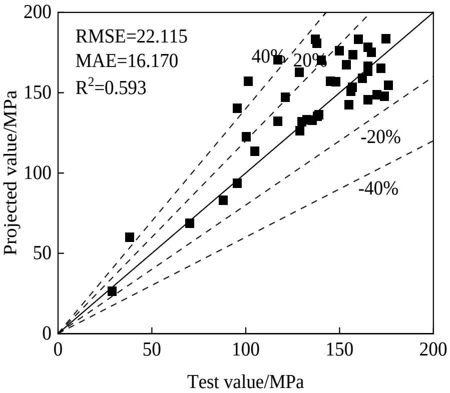
Figure1: Spearman's correlation coefficient between the characteristic variables

In order to train the model more conveniently and scientifically, and at the same time to eliminate the influence of variable distribution of the sample data set, 172 groups out of 214 sets of experimental data were randomly selected as the training set and the remaining 42 groups were used as the test set using the randperm function that comes with the Matlab software.

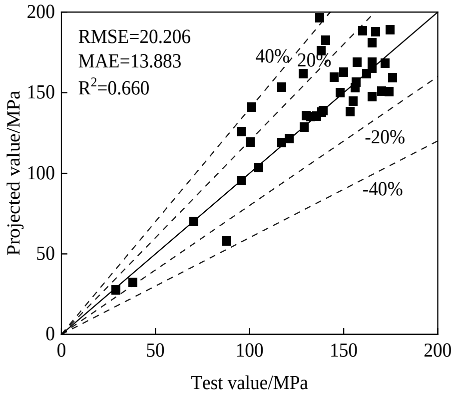
III. EXISTING RESIDUAL COMPRESSIVE STRENGTH CALCULATION MODEL

The existing residual compressive strength prediction of UHPC after high-temperature damage is mainly based on tests, and the expressions of the computational model functions are determined from the test data by regression fitting, so as to obtain the corresponding computational models of residual compressive strength. In order to further verify the applicability of the empirical calculation model under the effect of multiple factors, four first-order or multi-order combinations of the residual compressive strength empirical calculation models are selected in this paper, which are the empirical calculation models proposed by KAHANJI et al [9], GONG et al [10], ZHENG et al [33], and XIAO et al [34]. Figure 2 shows the scatter fit of the prediction results of each empirical computational model.

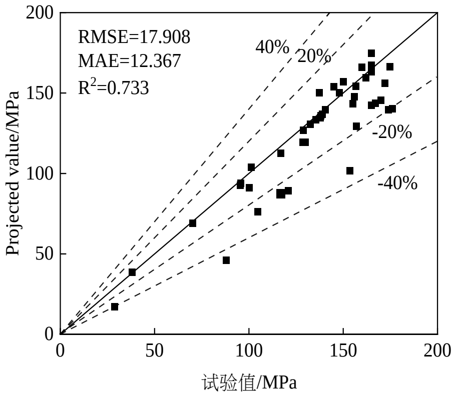
As can be seen from Figure 2, the model proposed by Gong et al [10] has the highest prediction accuracy, with an RMSE of 17.675, an MAE of 12.137, and an R^2 of 0.740, but none of them satisfies the requirement that the coefficient of determination of the engineering practice, R^2, is greater than 0.85. The computational models all showed high dispersion, indicating that after high-temperature damage, the residual compressive strength of UHPC under the effect of multiple factors is highly nonlinear, and the applicability of the empirical computational model under the effect of multiple factors is limited.



(a) KAHANJI model [9]



（b）GONG模型[10]



(d) XIAO model [34]

Figure2: Prediction results of the empirical calculation mode

IV. MACHINE LEARNING MODEL

4.1 BP neural network model

BP neural network in the training process, will first give the model random initial weights and thresholds, through the error reverse adjustment of the weights and thresholds of the neural network, until it reaches the training error requirements, the output of the trained model predictions [26]. Under a single hidden layer, as long as there are enough hidden layer nodes, the BP neural network has a strong nonlinear mapping ability, under a single hidden layer can be fitted to any nonlinear function [27], so this paper adopts a single hidden layer structure.

4.2 SSA-BP model

SSA model is a population intelligence optimization algorithm inspired by sparrow's foraging behavior and anti-predator behavior [28], which has high convergence and strong local search ability, and achieves complementarity with BP neural network which is easy to fall into local optimal solution, optimizes the weights and thresholds of BP neural network, and improves the global optimization performance of the model.

4.3 GA-BP model

GA model is a stochastic global search and optimization method developed to mimic the mechanism of biological evolution in nature, which automatically acquires and accumulates knowledge during the search process and adapts itself to the search process in order to find the best solution. By utilizing the parallelizability of GA algorithm, it can facilitate distributed computing, improve the robustness of the model, and increase the solution speed. Meanwhile, the GA algorithm has outstanding heuristic search advantages in multi-parameter optimization [29-30]. Therefore, the GA algorithm is used to optimize the BP neural network to predict the output under multivariate inputs.

4.4 SVR model

SVR model is a penalized learning algorithm by Vapnik et al [32] that introduces an insensitive loss function based on support vector machine classification to solve the regression fitting problem, and its basic idea is to map the input sample variables into a high-dimensional feature space, and search for an optimal hyperplane so that all the training samples are closest to this hyperplane.

V. MACHINE LEARNING MODEL PREDICTS RESULTS

The results of the machine learning model for predicting the compressive strength of UHPC after high temperature damage are shown in Figure 9 below.

- As can be seen from the error distribution graph, the error distribution curves of the training set of each machine learning model are in line with the characteristics of normal distribution, indicating that the models can accurately analyze the effect of the coupling of multiple input variables on the residual compressive strength of UHPC after high-temperature damage during the training process. The prediction error is basically controlled within 15%.
- Combined with the error distribution graph and the scatter fitting graph, it can be seen that the BP neural network model, although it has a high prediction accuracy during the training process, there are individual cases of large discrete errors.
- Compared with BP neural networks, SSA and GA optimization algorithms significantly improve the prediction performance of BP neural networks and make up for the shortcomings of BP neural network models in global optimization.
- Taken together, the optimal prediction model is the GA-BP model, the error distribution of the model approximates the standard normal distribution, and its evaluation indexes are 7.834 for RMSE, 6.408 for MAE, and 0.949 for R^2.
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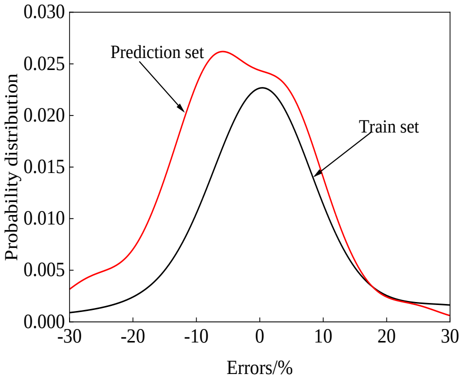
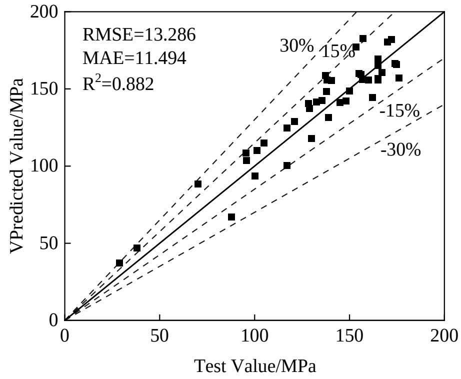
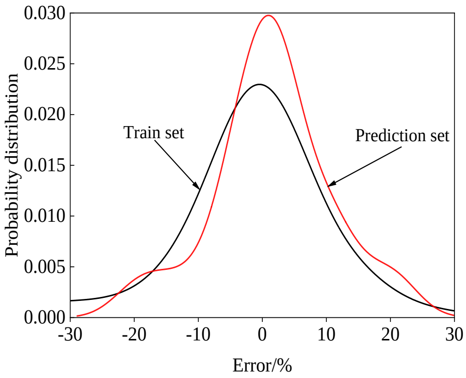


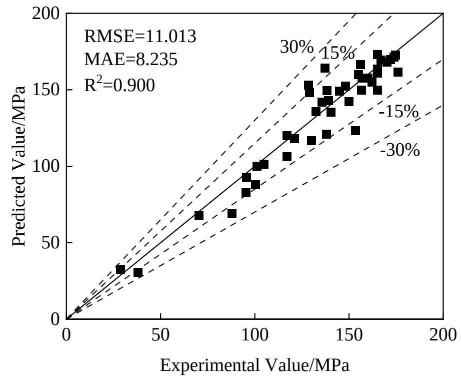
(a) Error distribution of the training set of the BP neural network model



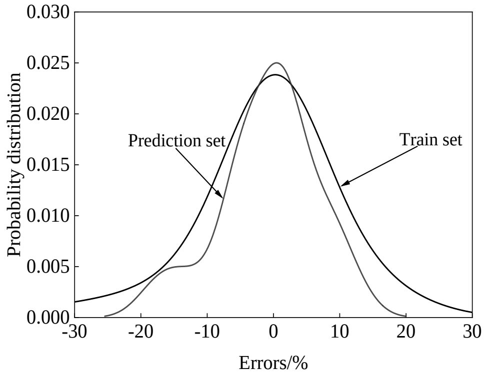
(b) Predicted and experimental values of BP neural network models



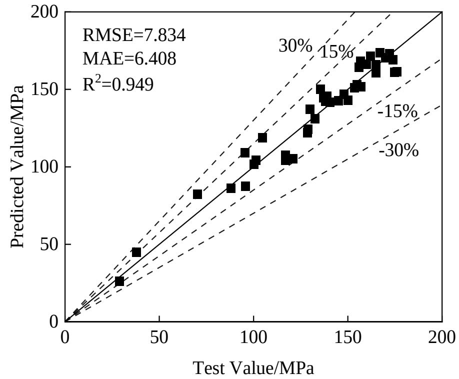
(c) Error distribution of SSA-BP model training set



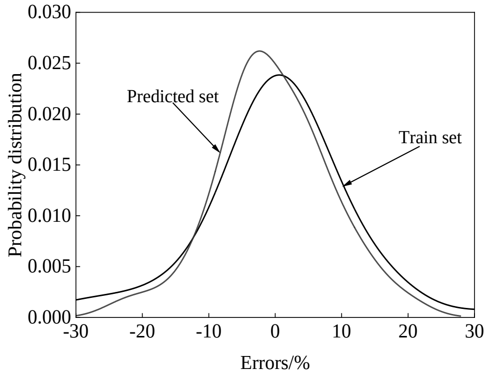
(d) Predicted and experimental values of the SSA-BP model



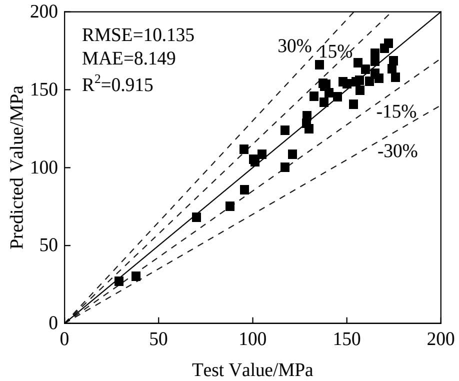
(e) Distribution of errors in the training set of the GA-BP model



(f) Predicted and experimental values of the GA-BP model



(g) Error distribution of the SVR model training set



(i) Predicted versus experimental values of the SVR model

Figure 9: Prediction results of different machine learning models

VI. CONCLUSION

In this paper, four models, namely, BP neural network, GA-BP, SSA-BP, and SVR model, were used to predict the residual compressive strength of UHPC after high-temperature damage, and in general, the prediction results of the experimental empirical calculation model were not ideal, presenting a large degree of dispersion; whereas, the machine learning model predicted a high degree of convergence, and the percentage of the prediction error was within 15%, and R2 were all greater than 0.85, and the prediction values were in close proximity with the experimental values are closer; among them, the GA-BP model has the best prediction results, and the error distribution is mainly concentrated in [-10%, 10%]. Therefore, the GA-BP model can predict the residual compressive strength of UHPC after high-temperature damage more accurately, which is suitable for the design and optimization of UHPC tests, reducing the workload of the test, and can provide a reference for the study of the influence of each raw material component of UHPC on the compressive strength after high-temperature damage.

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