Prediction of the post-fire flexural capacity of RC beam using GA-BPNN Machine Learning

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Abstract: To accurately predict the flexural capacity of post-fire RC beams is imperative for fire safety design. In this paper, the residual flexural capacity of post-fire RC beams is predicted based on a back-propagation (BP) neural network (NN) optimized by a genetic algorithm (GA). First, the temperature distribution of the beams was determined using the finite element analysis software ABAQUS, and the strength reduction factor of materials was determined. The flexural capacity of the RC beams after fire is calculated by the flexural strength reduction calculation model. The model is used to generate the training data for the NN. To enable machine learning, 480 datasets are produced, of which 360 datasets are used to train the network; the remaining 120 datasets are used to test the network. The predictive models are constructed using BPNN and GA-BPNN respectively. The prediction accuracy is evaluated by comparing the predicted values and the target values. The comparison shows that the GA-BPNN has a faster convergence speed, higher stability, and can reach the goal more times, reducing the possibility of BPNN falling into the local optimum and achieving the global optimum. The proposed GA-BPNN model for predicting the flexural capacity of post-fire RC beams provides a new approach for design practice.

Keywords: reinforced concrete, fire, flexural capacity, BP neural network, GA-BP neural network, prediction

1. **Introduction**

Fire is one of the most common disasters in today's society. Building Fire frequently occurs, accounting for approximately 80% of all fires (Xue et al. 2017). Buildings experience various degrees of damage after fire, and their mechanical properties should be fully evaluated to determine the safety of the structure after fire and provide reliable technical support for further retrofitting requirements. In fire the mechanical properties RC beam decrease significantly as the temperature increases (Felicetti et al. 2009; Annerel and Taerwe 2011).

To determine the residual flexural capacity, a large number of calculation processes are needed. The neural network (NN) can substitute human being to accurately predict the flexural capacity of the RC beams after a fire, thus avoiding complicated calculation processes (Naser et al. 2012; Xiang and Wang 2013).

Artificial NNs (ANNs) (Fu,2020) are mathematical or computational models that mimic the formation of the structure and the function of biological systems (Mao et al. 2011; Di Massimo et al. 1992; Zhang et al. 2003). ANNs have strong nonlinear

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analysis capabilities and can map a given input to the required output through training (Zhang et al. 2004). ANNs define relations in datasets and are suitable for problems that are difficult to solve using traditional mathematical methods. ANNs have wide application prospects in engineering. Sobhani et al. (2010) used NNs to study the compressive strength of no-slump concrete. Alshihri et al. (2009) established a predictive model of the compressive strength of structural light-weight concrete using ANN. Dwaikat (2008) conducted numerical simulations of fire-induced restraint effects in reinforced concrete beams based on NN. Kodur et al. (2004, 1998, 2003) predicted the fire resistance behavior of high-strength concrete columns using NNs. Abbasi (2005) used ANNs to establish a predictive model for glass fiber-reinforced plastic steel concrete beams. Erdem (2010) studied the prediction of the flexural capacity of RC plates after a fire using an ANN.

Back-propagation (BP) is a neural network algorithm whose process includes forward propagation of information and back propagation of errors. However, when Ling and Zhang (2014) used the BP NN to predict the price trend of gold, the convergence speed of the learning process of the BP NN appeared to be slower. To solve this problem, the global search ability of the genetic algorithm (GA) is often used to optimize the weight and threshold of BP NNs to improve their prediction ability (Ma and Shi 2004; Ding et al. 2011; Xu et al. 2014). Vinay Chandwani et al. (2015) used GAs to assist the ANN to simulate the slump of ready-mix concrete. The study showed that by hybridizing ANN with GA, the convergence speed of ANN and its accuracy of prediction can be improved. The trained hybrid model can be used to quickly predict the slump of concrete. Ahmed and Nehdi (2017) presented an approach to predicting the intrinsic self-healing in concrete using a hybrid GA–artificial NN. Yan et al. (2017,2016) combined the strong nonlinear mapping ability of ANN with the global searching ability of GA to study the diameter, surface, position, and embedment length of the steel, as well as the thickness of the concrete cover and concrete compressive strength on the influence of the glass fiber reinforced plastic (GFRP) bond strength of reinforcement and concrete, and they studied the anchorage reliability of GFRP steel given the factors of steel diameter, thickness of concrete cover, anchoring length, concrete compressive strength and ultimate yield strength of GFRP steel. However, few people use GA-BP NN to study the prediction of the flexural capacity of RC beams after fire controlled by multiple factors.

In this study, a new method for the rapid prediction the flexural capacity of post-fire reinforced concrete (RC) beams using GA-BP NN is developed. First, the temperature distribution of the beams was determined using the finite element analysis software ABAQUS, and the strength reduction factor of materials was determined. The flexural capacity of the RC beams after fire is calculated by the flexural strength reduction calculation model. The model is used to generate the training data for the NN. The flexural capacity of post-fire RC beams is predicted using a GA-BPNN. The predicted values obtained by the NN are compared to the target value, with small errors, demonstrating the accuracy of ANNs. The use of the GA-BPNN to predict the flexural capacity of post-fire RC beams can avoid the complex calculation used to reduce the workload for the study of post-fire building structures, providing a reliable basis for the strengthening of such structures, and save both time and resources.

2. Calculation model of the post-fire flexural capacity of RC beams

2.1 Heat transfer

Heat transfer comprises three key process, conduction, radiation and convection.

Conduction is the physical process of heat transfer from the presence of a temperature gradient. The high temperature of the fire acting on the surface of the reinforced concrete member is conducted into it by thermal conduction.

According to Fu (2016a,b, 2018), the thermal convection between the concrete surface of the fire field and the fire environment is as follows:

$$q = h\left(T_f - T_r\right) \tag{1}$$

where h is the convective heat transfer coefficient, T_f is the fire field temperature and T_r is the absolute temperature of receiving the surface.

The thermal radiation between the surface of concrete components and the fire environment is as follows:

$$q = \upsilon\gamma\left(T_f^{\,4} - T_r^{4}\right) \tag{2}$$

where υ is the surface emissivity, which, for concrete, is generally 0.3; and γ is the Stefan-Boltzmann constant (5.67×10^{-8} W/m^{2}K^4).

2.2 Thermal parameters

Heat transfer analysis requires the thermal parameters of the materials, including the heat conductivity, the specific heat capacity, and the density. The thermal parameters proposed in Eqs. (3) – (4) are used for the concrete in this study from BS EN1994-1-2 (BSI, 2013), and the steel adopts the thermal parameters proposed in Ref. (Lie and Irwin 1995).

The heat conduction rate of the concrete is as follows:

$$\lambda_c = 2 - 0.24\left(\frac{T}{120}\right) + 0.012\left(\frac{T}{120}\right)^2 \quad 20°C \le T \le 1200°C \tag{3}$$

where λ_c is the heat conduction rate of the concrete and T is the current temperature.

The specific heat capacity of the concrete is as follows:

$$c_c = 900 - 4\left(\frac{T}{120}\right)^2 + 80\left(\frac{T}{120}\right) \quad 20°C \le T \le 1200°C \tag{4}$$

where c_c is the specific heat capacity of the concrete.

The heat conduction rate of the steel is as follows:

$$\lambda_s = \begin{cases} 54 - 3.33\times10^{-2}T & 20°C \le T \le 800°C \\ 27.3 & 800°C \le T \le 1200°C \end{cases} \tag{5}$$

where λ_s is the heat conduction rate of the steel.

The specific heat capacity of the steel is as follows:

$$c_T = \begin{cases} 425 + 7.73\times10^{-1}T - 1.69\times10^{-3}T^2 + 2.22\times10^{-6}T^3 & 20°C \le T < 600°C \\ 666 + \dfrac{13002}{738 - T} & 600°C \le T < 735°C \\ 545 + \dfrac{17820}{T - 731} & 735°C \le T < 900°C \\ 650 & 900°C \le T < 1200°C \end{cases} \tag{6}$$

where c_T is the specific heat capacity of the steel. The specific heat capacity of the steel varies greatly with the increase of temperature, and the specific heat capacity increases rapidly; however, as the temperature continues to rise, the specific heat capacity of the steel rapidly decreases.

The ISO 834 fire curve used in this study is as follows (ISO, 1999):

$$T = T_0 + 345\lg(8t + 1) \tag{7}$$

where T_0 is the room temperature and t is the heating time.

2.3 Calculation of the post-fire flexural capacity

The mechanical properties of both reinforced steel and concrete were deteriorated after fires, which caused lower flexural capacity and thereby safety risks, therefore, the flexural capacity attenuation of components should be quantitatively identified. The temperature of post-fire RC beams was determined from the heat transferring analysis. The strength reduction equations were introduced to determine the post-fire strength of component materials. Then the post-fire residual flexural capacity of RC beams was analyzed.

After the thermal parameters of the concrete and the steel in the RC beam are determined according to sections 2.1 and 2.2, a heat transfer analysis is performed using ABAQUS to simulate the temperature field and to extract the temperatures of each point of the section at different times. According to the strength reduction method proposed in Niu et al (1990) and Yang et al. (2009), the compressive strength reduction factor of concrete and the yield strength reduction factor of steel at different temperatures are shown in Fig. 1. The flow chart for the flexural capacity of post-fire RC beams is shown in Fig. 2.

(Fig. 1)

According to Cai et al. (2019), the formula for calculating the flexural capacity in an RC beam after a fire is as follows:

$$M_{CT} = \alpha_1 \bar{\varphi}_{CT} f_c bx(h_0 - 0.5x) + \varphi'_{yT} f'_y A'_s (h_0 - a'_s) \tag{8}$$

where M_{CT} is the flexural capacity of the post-fire concrete beam at the maximum fire temperature of T℃; $\bar{\varphi}_{CT}$ is the strength reduction factor of concrete in the compressive zone; f_c is the compressive strength of the concrete at normal temperature; b is the sectional width of the beam; h_0 is the valid sectional height of the beam; α_1 = 1; x is the height of the compressed zone in the post-fire component; φ'_{yT} is the yield strength reduction factor of compressive reinforced steel; a'_s is the distance from the resultant force point of the compressive reinforced steel to the margins of the compressive section; f'_y is the yield strength of compressive reinforced steel at normal temperature; A'_s is the area of reinforced steel in the compressive zone.

(Fig. 2)

2.4 Verification of the post-fire flexural capacity of RC beams

The post-fire flexural capacity calculation model for RC beams was validated using the test data of specimen L5 and L9 in Ref. (Xu et al. 2013). They performed flexural tests for 7 RC beams after fire. the effects of fire exposure time，shear span ratio，reinforcement ratio and flange on the residual flexural capacity of the beans were analyzed. The reinforcement details of the specimen are illustrated in Fig.3. The reason that Tests L5 and L9 are selected for the validation is because they are expose to different fire durations. L5 is exposed to fire for 1 hour, and L9 is exposed to fire for 2 hours. The temperature field distribution is simulated using ABAQUS; then, in combination with Fig. 1, the compressive strength reduction factor and the yield strength reduction factor of the section of the beam after a fire are determined. The flexural capacity of specimen L5 was calculated with Eq. (8) as 194.45 kN, with a 0.79% error from that of specimen L5 in Ref. (Xu et al. 2013), which is 196 kN. The flexural capacity of specimen L9 was calculated with Eq. (8) as 164 kN, with a 1.70% error from that of specimen L9, which is 167 kN. The flexural capacity of the strength reduction model proposed in this paper agrees well with the Ref. (Xu et al. 2013) and indicates that the method can be applied to the calculation of the flexural capacity of RC beams after a fire.

(**Fig.** 3)

3 Artificial Neural Networks (ANNs)

3.1 Overview of ANNs

ANNs are mathematical models that mimic the structure and function of biological systems and are characterized by adaptivity, self-learning, nonlinear mapping, robustness, and fault tolerance (Lin et al. 2016). Based on modern neuroscience, ANNs mimic brain processing mechanisms to achieve the simulation effect. ANN models are independent of objects, targets, and datasets and have a strong nonlinear processing capability. Without the need for manually inputting specific formulas, the network can search for nonlinear relations between the inputs and outputs according to the existing test data and obtain a mathematical model that can map the intrinsic relations of the test data (Zhou and Ke 2016).

3.2 Introduction to the BPNN

The BPNN is currently the most widely used multilayer feedforward network structure (Cheng et al. 2015; Shen et al. 2008). In terms of learning rules, the BPNN is a supervised learning network, which can, when there is an unknown specific mapping relation between the inputs and outputs of the network, change its own structure, adjust the weights of neurons through the continuous learning of sample data, and finally create the correct mapping between the inputs and outputs of the network (Shang and Mao 2001; Zhao et al. 2019). Both working signals and error signals are propagated in the BPNN. The working signals are propagated forward from the input layer to the output layer, while the error signals are propagated backward (Yang et al. 2001). The two phases are repeated continuously to adjust the weights and thresholds of the network until the errors are minimized (Zhao et al. 2019).

The BPNN adopts the working principle of a multilayer feedforward network. Neurons in the hidden layer are connected to the inputs and outputs. The gradient learning method is used to adjust the weights in the training stage to minimize the errors between the actual outputs and target outputs. A given set of inputs [v_1, v_2, ..., v_j] are successively subjected to 2 basic mathematical operations to solve for the final output Z_j.

First, when the information passes through the input layer to the hidden layer, the bias of each neuron in the hidden layer is added to the product of the inputs and the sum of their respective weights to obtain the receiving vector U_j as follows:

$$U_j = \sum_{i=1}^{n} w_{ij} v_i + b_j \tag{9}$$

$$Z_j = f\left(U_j\right) \tag{10}$$

where $\left[w_{1j}, w_{2j}, \ldots, w_{ij}\right]$ is the weight vector of the j-th neuron between the input layer and the hidden layer, and b_j is the bias between the input layer and the hidden layer.

Assume that the architecture of the NN is 7-n-1 and the input layer is [v_1, v_2, ..., v_7]; then W_1 is the weight matrix from the input layer to the hidden layer, W_2 is the weight matrix from the hidden layer to the output layer, B_1 is the bias vector of the hidden layer, and B_2 is the bias vector of the output layer. According to the receiving vector U_1, the corresponding output Z_1 from the input layer to the hidden layer is obtained.

$$U_1 = W_1^T V + B_1 \tag{11}$$

Finally, the receiving vector U_2 is used to obtain the corresponding output Z_2 from the hidden layer to the output layer as follows: .

$$U_2 = W_2^T V_1 + K_2 = W_2^T\left(f\left(W_1^T V + B_1\right)\right) + B_2 \tag{12}$$

$$Z_2 = f_2\left(U_2\right) = f_2\left(W_2^T\left(f_1\left(W_1^T V + B_1\right)\right) + B_2\right) \tag{13}$$

where Z_2 is the prediction of the flexural capacity of the RC beam.

However, the traditional BP network inevitably has local convergency problems. During the learning process, the rate of decline and the rate of learning are slow, and a long-term error flat area is prone to appear. The choice of network structure is different, the network is too large, and the efficiency is not high in training.

3.3 Introduction to the GA-BPNN

The GA is a random search algorithm based on natural selection and the genetic mechanism of biological organisms. The GA searches for the optimal solution by simulating the natural evolution process. The method has the advantages of high robustness, strong global search ability, and simple calculations. The GA continuously evolves through the processes of selection, crossover, and mutation to obtain the optimal solution. Aiming at the shortcomings of the BPNN, a GA can be combined with BPNN to improve the structure, rules and weight threshold of an NN using the characteristics of the GA, thus improving the speed and accuracy of network prediction. The process of optimization of BPNN by the GA is shown in Fig. 4.

Step 1: Determine the topology, the weights, the thresholds, and the number of nodes of the BPNN.

Step 2: Collect raw data, such as fire duration and beam height. The original data is normalized and preprocessed, and the preprocessed value is used as input to the network.

Step 3: Select the GA parameters, initialize the population, and encode each individual as a string of real numbers, which are the connection weights between the input layer and the hidden layer, the threshold of the hidden layer, the connection weights between the hidden layer and the output layer, and the threshold of the output layer.

Step 4: Calculate the fitness of each individual of the population using the following function:

$$F = 1 \Big/ \sum_{i=1}^{N} abs\left(y_i^{'} - y_i\right) \tag{14}$$

where y_i is the target value and $y_i^{'}$ is the predicted output.

Step 5: Perform the GA operations of selection, crossover and mutation, successively, retaining the individuals with high fitness and eliminating those with low fitness.

The selection operation is as follows:

$$p_i = F_i \Big/ \sum_{i=1}^{N} F_i \tag{15}$$

where N is the population and F_{i} is the fitness of individual i.

The crossover operation is as follows:

Because real encoding is adopted for each individual, a real-coded crossover operator is used. The crossover operation at the j-th bits of the k-th chromosome a_k and the l-th chromosome a_1 is as follows:

$$\begin{aligned} a_{kj} &= a_{kj}\left(1-b_0\right) + a_{1j}b_0 \\ a_{1j} &= a_{1j}\left(1-b_0\right) + a_{kj}b_0 \end{aligned} \tag{16}$$

where b_0 is a random number in the range [0,1].

The mutation operation is as follows:

$$a_{ij} = \begin{cases} a_{ij} + \left(a_{ij} - a_{\max}\right) \times f\left(g\right) & r > 0.5 \\ a_{ij} + \left(a_{\min} - a_{ij}\right) \times f\left(g\right) & r \le 0.5 \end{cases} \tag{17}$$

$$f\left(g\right) = r_2 \times \left(1 - g/G_{\max}\right)^2 \tag{18}$$

where $a_{\max}$ and $a_{\min}$ are the upper and lower bounds of genes, respectively; r_2 is a random number; g is the current iterations; $G_{\max}$ is the maximum evolution and r is a random number in the range [0,1].

Step 6: Calculate the fitness of each individual. If there exists an individual in the new population that makes the network reach the global optimum or the number of iterations reaches the set maximum value, proceed to the next step; otherwise, return to Step 5.

Step 7: Output the individual with the highest fitness and obtain the weights and thresholds that result in the global optimum.

Step 8: Assign the optimized weights and thresholds to the BPNN. Then, the reserved training samples are used to train the BPNN until the errors are within the preset error range, thus completing the prediction for the flexural capacity of the post-fire RC beam.

Step 9: Input the preprocessed data into the trained GA-BPNN, output the data from the network, and inversely normalize the data to obtain the predicted values of the flexural capacity of the post-fire RC beam.

Fig. 4

4 The NN model for predicting the post-fire flexural capacity of an RC beam

4.1 Model development

As we all know, fire experiments are very expensive and require a lot of time. In addition, the number of dedicated research facilities and test furnaces is limited. These problems pose obstacles to the flexural, shear, axial tests of reinforced concrete members under high temperature. Therefore, in this paper, an alternative method is proposed. According to the calculation model of the flexural strength reduction after a fire proposed in section 2.3, the theoretical value of the flexural capacity of the RC beam after fire is obtained. The theoretical value is used as the training data of the NN.

The developed BPNN and GA-BPNN models have 7 input neurons and 1 output neuron. The input layer is the main influencing factor on the flexural capacity of the RC beams after fire, including 7 parameters: the beam width, the beam height, the fire time, the cross-sectional area of the tensile reinforcement, the concrete compressive strength, the tensile strength of the tensile reinforcement, and the thickness of the concrete cover. The number of neurons in the hidden layer is 10 and the output layer is the flexural capacity of the RC beam after a fire. The topology of the BPNN is shown in Fig. 5. The values of the input layer parameters were t (5, 10, 15, 20, 25, 30, 35, 40, 45, 50, 55, 60, 65, 70, 75, 80, 85, 90, 95, 100, 105, 110, 115, 120min), b (200mm), h (400, 450, 500, 550, 600mm), As (628, 760, 982, 1232mm^2), fc (24.23, 28.03, 32.05, 36.05, 39.82, 42.92MPa), fy (332.85, 381.65, 443.80, 554.75MPa), c (25, 30, 35, 40, 45mm).

Fig. 5

4.2 Model algorithm

In this study, the GA-BPNN prediction model is used. The tangent sigmoid function is adopted as the transfer function for the neurons in the hidden layer. The sigmoid function is expressed as follows:

$$g(v)=\frac{1}{1+e^{-v}} \tag{19}$$

The outputs are controlled in the range [0,1]. Transformation is performed to prevent the excessively large absolute value of the net input from saturating the output of the neuron and subsequently adjusting the weights to enter the flat area of the error surface. A pure linear transformation function, the purelin function, is used for the neurons in the output layer to improve the prediction accuracy of the network. The Initff function is selected as the initialization function, and the Trainlm function is selected as the training function. The Levenberg-Marquard algorithm is adopted, which has a high gradient descent speed and a small number of training steps (Hecht-Nielsen 1992).

The input and output data are preprocessed prior to training to accelerate the convergence of the training network and to obtain more accurate prediction results by arranging the data in the same order of magnitude during operation. Data normalization is a commonly used data preprocessing method to transform the input and output data to values in the interval [0,1], shown in Eq. (20) as follows:

$$\overline{v}_i=\frac{v_i-v_{\min}}{v_{\max}-v_{\min}} \tag{20}$$

where v_i are the input/output data, $v_{\min}$ is the minimum range of data change, and $v_{\max}$ is the maximum range of data change.

4.3 Training data

The selection of training samples affects the accuracy of the NN. The prediction model of the flexural capacity of RC beams after a fire provided 480 datasets using the calculation method proposed in section 2.3. Among them, the first 360 datasets were used for network training and the last 120 datasets were used for network testing. . In training sets, the varied parameters and its range： *t* (5, 10, 15, 20, 25, 30, 35, 40, 45, 50, 55, 60, 65, 70, 75, 80, 85, 90, 95, 100, 105, 110, 115, 120min), *b* (200mm), *h* (400, 450, 500, 600mm), *As* (628, 982, 1232mm^2), *fc* (24.23, 28.03, 36.05, 39.82, 42.92MPa), *fy* (332.85, 381.65, 554.75MPa), *c* (25, 30, 40, 45mm); In testing sets, the varied parameters and its range: *t* (5, 10, 15, 20, 25, 30, 35, 40, 45, 50, 55, 60, 65, 70, 75, 80, 85, 90, 95, 100, 105, 110, 115, 120min), *b* (200mm), *h* (500, 550mm), *As* (760, 982mm^2), *fc* (28.03, 32.05MPa), *fy* (381.65, 443.80MPa), *c* (25, 35mm). The training target error is 0.0001, the maximum number of training steps is 1000, and the learning rate is 0.1. In the GA-BPNN prediction model used in this study, the number of neurons in the hidden layer is 10, and the network structure is 7 - 10 - 1; thus, the weight and the threshold are adjusted as shown in Eqs. (21) - (24). The parameters of the GA are shown in Table 1, and the predicted samples are shown in Table 2.

(Table 1)

$$W_1 = \begin{pmatrix} 0.1452 & 0.8605 & -0.2432 & 0.2343 & 0.7056 & -0.6470 & 0.5659 \\ 0.0931 & 0.4168 & 0.5095 & -0.6050 & -0.1141 & -0.2291 & 0.9709 \\ 0.2850 & -0.8223 & -0.2377 & -0.7271 & 0.8383 & -0.0898 & 0.0560 \\ 0.7729 & 0.4409 & -0.2259 & -0.6032 & 0.7508 & -0.1719 & 0.0003 \\ 0.0729 & -0.9962 & 0.6954 & 0.1888 & 0.3656 & -0.5325 & -0.5049 \\ 0.4299 & 0.6596 & 0.2856 & 0.1927 & -0.0686 & 0.2241 & 0.5440 \\ -0.6993 & -0.9837 & 0.3221 & -0.8106 & 0.5365 & -0.5613 & -0.7259 \\ 0.5130 & -0.2736 & 0.8373 & 0.9135 & -0.5422 & 0.9641 & 0.1041 \\ 0.5436 & -0.5641 & 0.8727 & -0.5856 & 0.2048 & 0.7321 & 0.2472 \\ -0.9972 & -0.4054 & -0.3021 & 0.9476 & 0.4698 & 0.0223 & 0.0123 \end{pmatrix} \quad (21)$$

$$B_1^T = \left(-0.0973 \;\; -0.6616 \;\; 0.6662 \;\; 0.4355 \;\; -0.5157 \;\; 0.0273 \;\; -0.5978 \;\; -0.7636 \;\; -0.7224 \;\; 0.6833\right) \quad (22)$$

$$W_2 = \left(0.7974 \;\; 0.8701 \;\; 0.3143 \;\; -0.2621 \;\; -0.4665 \;\; -0.3173 \;\; 0.5124 \;\; 0.6922 \;\; -0.5729 \;\; 0.6179\right) \quad (23)$$

$$B_2 = \left(-0.4996\right) \quad (24)$$

(Table 2)

5 GA-BPNN prediction and analysis

To verify the efficiency of the GA-BPNN, the performance of the model is evaluated using the relative error (E_{MR}) and the root-mean-square error ($RMSE$). The correlation coefficient (R^2) is introduced to test the robustness of the NN model.

$$E_{MR} = \left[\sum_{i=1}^{m} \frac{\left| y_i - y_i^{'} \right|}{y_i} \Big/ m \right] \times 100\% \quad (25)$$

$$RMSE = \sqrt{\frac{1}{N} \sum_{i=1}^{N} \left(y_i^{'} - y_i \right)^2} \quad (26)$$

$$R^2 = 1 - \left(\sum_{i=1}^{N} \left(y_i^{'} - y_i \right)^2 \Big/ \sum_{i=1}^{N} \left(y_i^{'} \right)^2 \right) \quad (27)$$

where y_i is the target value, and $y_i^{'}$ is the predicted value.

Fig. 7 shows the Comparison of the predicted values of BPNN and GA-BPNN and Fig. 8 shows the comparison of the absolute error values predicted by BPNN and GA-BPNN

The data in Fig. 7 show that, after training, there is little difference in the flexural capacity of the post-fire RC beams as predicted by the BPNN and GA-BPNN prediction models and the target values. The values predicted by the GA-BPNN model are nearer the target values, indicating the higher accuracy of the GA-BPNN model.In Fig.8, the maximum absolute error of the GA-BPNN prediction is 12.64, the minimum is -9.82, the maximum absolute error of the BPNN is 18.45, and the minimum is -13.89, and the amplitude and range of the GA-BPNN absolute error curve are small, indicating that the GA-BPNN prediction is more stable, which reflects the generalization ability of the GA-BPNN is stronger. Figure 9 is the comparison of GA-BPNN prediction relative error and BPNN prediction relative error, whose X-axis is prediction sample and Y-axis is relative error. Figure 9 shows the E_{MR} values of the GA-BPNN model is less than 8.1% and the BPNN model is less than 12%, while overall, the E_{MR} of the GA-BPNN model is better than that of the BPNN model.

Figures 10, 11, and 12 show the correlation between the target values and the values predicted by the GA-BPNN model using the training samples, all samples, and the testing samples, respectively. The R^2 of the testing samples is 0.99886, the R^2 of the training samples is 0.99526, and the R^2 of all samples is 0.99617. Figure. 13 shows the correlation between the target values and the values predicted by the BPNN with an R^2 of 0.99721. The closer R^2 is to 1, the better the fit. The results show that the R^2 of the testing samples of the GA-BPNN is closer to 1 than that of the BPNN, indicating the improved generalization ability of the GA-BPNN.

From Table 3, the average relative error of the GA-BP neural network prediction model is 2.81%, the RMSE is 4.70, and the average relative error of the BP neural network prediction model is 4.41%, with an RMSE of 7.39. The data demonstrate that the prediction performance of the GA-BPNN model is more stable than that of the BPNN model.

In Table 4, the training time of the GA-BPNN and BPNN is almost the same, but the training accuracy of the GA-BPNN is much better than that of the BPNN, so the use of the GA-BPNN can better predict the RC beam flexural capacity after fire. The BPNN learning rate is slow, and the training efficiency is not high. While the GA-BPNN has a faster convergence speed, higher stability, and can reach the goal more times, reducing the possibility of BPNN falling into the local optimum and achieving the global optimum.

In summary, the calculation results prove that it is feasible to use GA-BPNNs to predict the flexural capacity of post-fire RC beams.

Fig. 6-13

Table 3

Table 4

6. Conclusion

In this paper. a GA-optimized BPNN is proposed to predict the flexural capacity of post-fire RC beams. The optimal weights and thresholds of the BPNN are obtained through the GA. The prediction model is trained and then tested to eventually obtain the global optimal predicted values. Finally, the values predicted by the GA-BPNN and the BPNN are compared, and the following conclusions are obtained:

(1) The analysis results show that both the BPNN and the GA-BPNN can predict the flexural capacity of RC beams after fire exposure.

(2) The GA-BPNN prediction model proposed in this paper for calculating the flexural capacity of post-fire RC beams combines the nonlinear mapping capability of ANNs and the global search capability of GA. The predicted values of the GA-BPNN model fit well with the target values. The E_{MR} of the predicted values of the NN and the target values are always less than 8.1% and less than that of the BPNN, the R^2 of the training samples and the test samples are 0.99526 and 0.99886, respectively, indicating that the GA-BP prediction model has higher robustness and fitting ability.

(3) The prediction for the flexural capacity of post-fire RC beams based on the GA-BPNN has good generalization ability, and can be used as a feasible method for RC beam flexural capacity research after fire.

(4) With the increase of the fire time, the strength reduction factor of the concrete in the compression zone $\bar{\varphi}_{CT}$ and the yield strength reduction factor of compressive reinforced steel φ'_{yT} decrease, so that the flexural capacity of RC beams after fire decreases. In addition, during the temperature increase stage, the protective capability provided by the concrete cover on the RC beam can decrease from fire damage.

In this study, the ISO834 international temperature rise curve is used to establish the RC beams model according to the input parameters and adopted to simulate the fire condition of the RC beams when the fire occurs, and the flexural capacity of the RC beams after fire conditions is obtained. However, in the real time fire situation, it is difficult to predict the flexural capacity of the RC beams because of the complex fire conditions of building components. The prediction model proposed in this study can only provide preliminary theoretical data for the damage assessment and reinforcement of post-fire beams, and further research is needed.

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Authors' contributions

BC and FF designed the research methodology; GLP performed the analysis, GLP and FF draft the manuscript; BC and FF reviewed the manuscript. All authors read and approved the final manuscript.

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Availability of data and materials

All data, code for the machine learning that support the findings of this study are available from the corresponding author upon reasonable request.

They are:

Training data for machine learning

Prediction result data for machine learning

Code for machine learning

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Competing interests

The authors declare that they have no competing interests.

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Table

Table 1 GA parameters

Population size	Number of evolutions	Crossover probability	Mutation probability
50	20	0.6	0.2

Table 2 Prediction samples

No	*t* (min	*b* (mm	*h* (mm	A_s (mm^2	f_c (MPa	f_y (MPa	*c* (mm	*Targe* (kNm	*GA-BP-sim* (kNm)	*e* (%)
1	5	200	550	982	28.03	381.6	25	181.6	177.20	2.4
2	10	200	550	982	28.03	381.6	25	179.0	175.72	1.8
3	15	200	550	982	28.03	381.6	25	176.5	173.47	1.7
4	20	200	550	982	28.03	381.6	25	174.1	171.21	1.6
5	25	200	550	982	28.03	381.6	25	171.5	169.83	1.0
6	30	200	550	982	28.03	381.6	25	169.5	168.15	0.8
7	35	200	550	982	28.03	381.6	25	167.6	166.33	0.7
8	40	200	550	982	28.03	381.6	25	167.1	164.43	1.6
9	45	200	550	982	28.03	381.6	25	161.6	162.88	0.7
10	50	200	550	982	28.03	381.6	25	156.7	159.30	1.6
11	55	200	550	982	28.03	381.6	25	152.7	156.45	2.4
12	60	200	550	982	28.03	381.6	25	149.4	154.82	3.6
.	.	.	.	.	.	.	.	.	.	.
.	.	.	.	.	.	.	.	.	.	.
.	.	.	.	.	.	.	.	.	.	.
97	5	200	500	982	28.03	381.6	35	160.2	165.29	3.1
98	10	200	500	982	28.03	381.6	35	159.1	163.39	2.6
99	15	200	500	982	28.03	381.6	35	157.7	161.56	2.4
10	20	200	500	982	28.03	381.6	35	156.1	159.77	2.3
10	25	200	500	982	28.03	381.6	35	154.4	158.02	2.3
10	30	200	500	982	28.03	381.6	35	152.9	156.27	2.1
10	35	200	500	982	28.03	381.6	35	151.1	154.51	2.2
10	40	200	500	982	28.03	381.6	35	149.6	152.74	2.0
10	45	200	500	982	28.03	381.6	35	148.2	150.93	1.7
10	50	200	500	982	28.03	381.6	35	147.1	149.09	1.2
10	55	200	500	982	28.03	381.6	35	145.9	147.19	0.8
10	60	200	500	982	28.03	381.6	35	144.7	145.25	0.3
10	65	200	500	982	28.03	381.6	35	143.5	143.24	0.2
11	70	200	500	982	28.03	381.6	35	143.2	141.16	1.4
11	75	200	500	982	28.03	381.6	35	141.1	139.01	1.4
11	80	200	500	982	28.03	381.6	35	137.6	136.78	0.6
11	85	200	500	982	28.03	381.6	35	135.9	134.46	1.0
11	90	200	500	982	28.03	381.6	35	133.6	132.04	1.1
11	95	200	500	982	28.03	381.6	35	131.1	129.52	1.2
11	100	200	500	982	28.03	381.6	35	129.1	126.87	1.7
11	105	200	500	982	28.03	381.6	35	126.9	124.09	2.2
11	110	200	500	982	28.03	381.6	35	124.9	121.16	3.0
11	115	200	500	982	28.03	381.6	35	122.7	118.06	3.8
12	120	200	500	982	28.03	381.6	35	120.9	115.62	4.3

Target and *GA-BP-simu* are the target value and predicted value of the reinforced concrete strength, respectively; *e*=| *Target* –*GA-BP-simu*|/ *Target*

Table 3 Analysis of the predicted values of testing samples

	Maximum relative error /%	Minimum relative error /%	Mean relative error /%	RMSE	R^2
BP	11.73	0.0078	4.41	7.39	0.99721
GA-BP	8.10	0.17	2.81	4.70	0.99886

Table 4 Training performance comparison of GA-BPNN and BPNN

	Training time（s）	Training accuracy
BP	3	0.015
GA-BP	3.2	0.0043

List of Figure captions