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

52 Back-propagation (BP) is a neural network algorithm whose process includes
53 forward propagation of information and back propagation of errors. However, when
54 Ling and Zhang (2014) used the BP NN to predict the price trend of gold, the
55 convergence speed of the learning process of the BP NN appeared to be slower. To
56 solve this problem, the global search ability of the genetic algorithm (GA) is often
57 used to optimize the weight and threshold of BP NNs to improve their prediction
58 ability (Ma and Shi 2004; Ding et al. 2011; Xu et al. 2014). Vinay Chandwani et al.
59 (2015) used GAs to assist the ANN to simulate the slump of ready-mix concrete. The
60 study showed that by hybridizing ANN with GA, the convergence speed of ANN and
61 its accuracy of prediction can be improved. The trained hybrid model can be used to
62 quickly predict the slump of concrete. Ahmed and Nehdi (2017) presented an
63 approach to predicting the intrinsic self-healing in concrete using a hybrid GA–
64 artificial NN. Yan et al. (2017,2016) combined the strong nonlinear mapping ability of
65 ANN with the global searching ability of GA to study the diameter, surface, position,
66 and embedment length of the steel, as well as the thickness of the concrete cover and
67 concrete compressive strength on the influence of the glass fiber reinforced plastic
68 (GFRP) bond strength of reinforcement and concrete, and they studied the anchorage
69 reliability of GFRP steel given the factors of steel diameter, thickness of concrete
70 cover, anchoring length, concrete compressive strength and ultimate yield strength of
71 GFRP steel. However, few people use GA-BP NN to study the prediction of the
72 flexural capacity of RC beams after fire controlled by multiple factors.

73 In this study, a new method for the rapid prediction the flexural capacity of
74 post-fire reinforced concrete (RC) beams using GA-BP NN is developed. First, the
75 temperature distribution of the beams was determined using the finite element
76 analysis software ABAQUS, and the strength reduction factor of materials was
77 determined. The flexural capacity of the RC beams after fire is calculated by the
78 flexural strength reduction calculation model. The model is used to generate the
79 training data for the NN. The flexural capacity of post-fire RC beams is predicted
80 using a GA-BPNN. The predicted values obtained by the NN are compared to the
81 target value, with small errors, demonstrating the accuracy of ANNs. The use of the
82 GA-BPNN to predict the flexural capacity of post-fire RC beams can avoid the
83 complex calculation used to reduce the workload for the study of post-fire building

84 structures, providing a reliable basis for the strengthening of such structures, and save
85 both time and resources.

86

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

88 2.1 Heat transfer

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

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

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

$$95 \quad q = h(T_f - T_r) \quad (1)$$

96 where h is the convective heat transfer coefficient, T_f is the fire field temperature

97 and T_r is the absolute temperature of receiving the surface.

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

$$100 \quad q = \nu\gamma(T_f^4 - T_r^4) \quad (2)$$

101 where ν is the surface emissivity, which, for concrete, is generally 0.3; and γ is the

102 Stefan-Boltzmann constant ($5.67 \times 10^{-8} \text{ W/m}^2\text{K}^4$).

103 2.2 Thermal parameters

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

109 The heat conduction rate of the concrete is as follows:

$$110 \quad \lambda_c = 2 - 0.24\left(\frac{T}{120}\right) + 0.012\left(\frac{T}{120}\right)^2 \quad 20^\circ\text{C} \leq T \leq 1200^\circ\text{C} \quad (3)$$

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

113 The specific heat capacity of the concrete is as follows:

$$114 \quad c_c = 900 - 4\left(\frac{T}{120}\right)^2 + 80\left(\frac{T}{120}\right) \quad 20^\circ\text{C} \leq T \leq 1200^\circ\text{C} \quad (4)$$

115 where c_c is the specific heat capacity of the concrete.

116 The heat conduction rate of the steel is as follows:

$$117 \quad \lambda_s = \begin{cases} 54 - 3.33 \times 10^{-2}T & 20^\circ\text{C} \leq T \leq 800^\circ\text{C} \\ 27.3 & 800^\circ\text{C} \leq T \leq 1200^\circ\text{C} \end{cases} \quad (5)$$

118 where λ_s is the heat conduction rate of the steel.

119 The specific heat capacity of the steel is as follows:

$$120 \quad c_T = \begin{cases} 425 + 7.73 \times 10^{-1}T - 1.69 \times 10^{-3}T^2 + 2.22 \times 10^{-6}T^3 & 20^\circ\text{C} \leq T < 600^\circ\text{C} \\ 666 + \frac{13002}{738 - T} & 600^\circ\text{C} \leq T < 735^\circ\text{C} \\ 545 + \frac{17820}{T - 731} & 735^\circ\text{C} \leq T < 900^\circ\text{C} \\ 650 & 900^\circ\text{C} \leq T < 1200^\circ\text{C} \end{cases} \quad (6)$$

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

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

$$126 \quad T = T_0 + 345 \lg(8t + 1) \quad (7)$$

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

128 2.3 Calculation of the post-fire flexural capacity

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

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

144 (Fig. 1)

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

$$147 \quad M_{CT} = \alpha_1 \bar{\varphi}_{CT} f_c b x (h_0 - 0.5x) + \varphi'_{yT} f'_y A'_s (h_0 - a'_s) \quad (8)$$

148 where M_{CT} is the flexural capacity of the post-fire concrete beam at the maximum
149 fire temperature of $T^\circ\text{C}$; $\bar{\varphi}_{CT}$ is the strength reduction factor of concrete in the
150 compressive zone; f_c is the compressive strength of the concrete at normal
151 temperature; b is the sectional width of the beam; h_0 is the valid sectional height of the
152 beam; $\alpha_1 = 1$; x is the height of the compressed zone in the post-fire component; φ'_{yT}
153 is the yield strength reduction factor of compressive reinforced steel; a'_s is the
154 distance from the resultant force point of the compressive reinforced steel to the
155 margins of the compressive section; f'_y is the yield strength of compressive
156 reinforced steel at normal temperature; A'_s is the area of reinforced steel in the

157 compressive zone.

158
159 (Fig. 2)

160 161 162 **2.4 Verification of the post-fire flexural capacity of RC beams**

163 The post-fire flexural capacity calculation model for RC beams was validated
164 using the test data of specimen L5 and L9 in Ref. (Xu et al. 2013). They performed
165 flexural tests for 7 RC beams after fire. the effects of fire exposure time, shear span
166 ratio, reinforcement ratio and flange on the residual flexural capacity of the beams
167 were analyzed. The reinforcement details of the specimen are illustrated in Fig.3. The
168 reason that Tests L5 and L9 are selected for the validation is because they are expose
169 to different fire durations. L5 is exposed to fire for 1 hour, and L9 is exposed to fire
170 for 2 hours. The temperature field distribution is simulated using ABAQUS; then, in
171 combination with Fig. 1, the compressive strength reduction factor and the yield
172 strength reduction factor of the section of the beam after a fire are determined. The
173 flexural capacity of specimen L5 was calculated with Eq. (8) as 194.45 kN, with a
174 0.79% error from that of specimen L5 in Ref. (Xu et al. 2013), which is 196 kN. The
175 flexural capacity of specimen L9 was calculated with Eq. (8) as 164 kN, with a 1.70%
176 error from that of specimen L9, which is 167 kN. The flexural capacity of the strength
177 reduction model proposed in this paper agrees well with the Ref. (Xu et al. 2013) and
178 indicates that the method can be applied to the calculation of the flexural capacity of
179 RC beams after a fire.

180 (Fig. 3)

181 **3 Artificial Neural Networks (ANNs)**

182 **3.1 Overview of ANNs**

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

192 **3.2 Introduction to the BPNN**

193 The BPNN is currently the most widely used multilayer feedforward network
194 structure (Cheng et al. 2015; Shen et al. 2008). In terms of learning rules, the BPNN is
195 a supervised learning network, which can, when there is an unknown specific
196 mapping relation between the inputs and outputs of the network, change its own
197 structure, adjust the weights of neurons through the continuous learning of sample
198 data, and finally create the correct mapping between the inputs and outputs of the
199 network (Shang and Mao 2001; Zhao et al. 2019). Both working signals and error
200 signals are propagated in the BPNN. The working signals are propagated forward

201 from the input layer to the output layer, while the error signals are propagated
 202 backward (Yang et al. 2001). The two phases are repeated continuously to adjust the
 203 weights and thresholds of the network until the errors are minimized (Zhao et al.
 204 2019).

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

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

$$214 \quad U_j = \sum_{i=1}^n w_{ij} v_i + b_j \quad (9)$$

$$215 \quad Z_j = f(U_j) \quad (10)$$

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

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

$$223 \quad U_1 = W_1^T V + B_1 \quad (11)$$

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

$$226 \quad U_2 = W_2^T V_1 + K_2 = W_2^T (f(W_1^T V + B_1)) + B_2 \quad (12)$$

$$227 \quad Z_2 = f_2(U_2) = f_2(W_2^T (f_1(W_1^T V + B_1)) + B_2) \quad (13)$$

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

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

233 3.3 Introduction to the GA-BPNN

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

242 prediction. The process of optimization of BPNN by the GA is shown in Fig. 4.

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

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

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

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

$$255 \quad F = 1 / \sum_{i=1}^N \text{abs}(y_i' - y_i) \quad (14)$$

256 where y_i is the target value and y_i' is the predicted output.

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

260 The selection operation is as follows:

$$261 \quad p_i = F_i / \sum_{i=1}^N F_i \quad (15)$$

262 where N is the population and F_i is the fitness of individual i .

263 The crossover operation is as follows:

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

$$267 \quad \begin{aligned} a_{kj} &= a_{kj}(1-b_0) + a_{lj}b_0 \\ a_{lj} &= a_{lj}(1-b_0) + a_{kj}b_0 \end{aligned} \quad (16)$$

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

269 The mutation operation is as follows:

$$270 \quad a_{ij} = \begin{cases} a_{ij} + (a_{ij} - a_{\max}) \times f(g) & r > 0.5 \\ a_{ij} + (a_{\min} - a_{ij}) \times f(g) & r \leq 0.5 \end{cases} \quad (17)$$

$$271 \quad f(g) = r_2 \times (1 - g/G_{\max})^2 \quad (18)$$

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

275 Step 6: Calculate the fitness of each individual. If there exists an individual in the

276 new population that makes the network reach the global optimum or the number of
277 iterations reaches the set maximum value, proceed to the next step; otherwise, return
278 to Step 5.

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

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

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

288

289

Fig. 4

290

291 **4 The NN model for predicting the post-fire flexural capacity of an RC beam**

292 **4.1 Model development**

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

301 The developed BPNN and GA-BPNN models have 7 input neurons and 1 output
302 neuron. The input layer is the main influencing factor on the flexural capacity of the
303 RC beams after fire, including 7 parameters: the beam width, the beam height, the fire
304 time, the cross-sectional area of the tensile reinforcement, the concrete compressive
305 strength, the tensile strength of the tensile reinforcement, and the thickness of the
306 concrete cover. The number of neurons in the hidden layer is 10 and the output layer
307 is the flexural capacity of the RC beam after a fire. The topology of the BPNN is
308 shown in Fig. 5. The values of the input layer parameters were t (5, 10, 15, 20, 25, 30,
309 35, 40, 45, 50, 55, 60, 65, 70, 75, 80, 85, 90, 95, 100, 105, 110, 115, 120min), b
310 (200mm), h (400, 450, 500, 550, 600mm), A_s (628, 760, 982, 1232mm²), f_c (24.23,
311 28.03, 32.05, 36.05, 39.82, 42.92MPa), f_y (332.85, 381.65, 443.80, 554.75MPa), c (25,
312 30, 35, 40, 45mm).

313

314

Fig. 5

315

316 **4.2 Model algorithm**

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

320
$$g(v) = \frac{1}{1+e^{-v}} \quad (19)$$

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

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

335
$$\bar{v}_i = \frac{v_i - v_{\min}}{v_{\max} - v_{\min}} \quad (20)$$

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

337 v_{\max} is the maximum range of data change.

338 4.3 Training data

339 The selection of training samples affects the accuracy of the NN. The prediction
 340 model of the flexural capacity of RC beams after a fire provided 480 datasets using
 341 the calculation method proposed in section 2.3. Among them, the first 360 datasets
 342 were used for network training and the last 120 datasets were used for network
 343 testing. . In training sets, the varied parameters and its range: t (5, 10, 15, 20, 25, 30,
 344 35, 40, 45, 50, 55, 60, 65, 70, 75, 80, 85, 90, 95, 100, 105, 110, 115, 120min), b
 345 (200mm), h (400, 450, 500, 600mm), A_s (628, 982, 1232mm²), f_c (24.23, 28.03, 36.05,
 346 39.82, 42.92MPa), f_y (332.85, 381.65, 554.75MPa), c (25, 30, 40, 45mm); In testing
 347 sets, the varied parameters and its range: t (5, 10, 15, 20, 25, 30, 35, 40, 45, 50, 55, 60,
 348 65, 70, 75, 80, 85, 90, 95, 100, 105, 110, 115, 120min), b (200mm), h (500, 550mm),
 349 A_s (760, 982mm²), f_c (28.03, 32.05MPa), f_y (381.65, 443.80MPa), c (25, 35mm). The
 350 training target error is 0.0001, the maximum number of training steps is 1000, and the
 351 learning rate is 0.1. In the GA-BPNN prediction model used in this study, the number
 352 of neurons in the hidden layer is 10, and the network structure is 7 - 10 - 1; thus, the
 353 weight and the threshold are adjusted as shown in Eqs. (21) - (24). The parameters of
 354 the GA are shown in Table 1, and the predicted samples are shown in Table 2.

355 (Table 1)

356

357

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

358

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

359

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

360

(23)

361

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

362

(Table 2)

363

364

365

366 5 GA-BPNN prediction and analysis

367

368 To verify the efficiency of the GA-BPNN, the performance of the model is
 369 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.

370

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

371

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

372

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

373

where y_i is the target value, and y_i' is the predicted value.

374

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

377

378 The data in Fig. 7 show that, after training, there is little difference in the flexural
 379 capacity of the post-fire RC beams as predicted by the BPNN and GA-BPNN
 380 prediction models and the target values. The values predicted by the GA-BPNN model
 381 are nearer the target values, indicating the higher accuracy of the GA-BPNN model. In
 382 Fig. 8, the maximum absolute error of the GA-BPNN prediction is 12.64, the
 383 minimum is -9.82, the maximum absolute error of the BPNN is 18.45, and the
 384 minimum is -13.89, and the amplitude and range of the GA-BPNN absolute error
 385 curve are small, indicating that the GA-BPNN prediction is more stable, which
 386 reflects the generalization ability of the GA-BPNN is stronger. Figure 9 is the
 387 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}
 388 values of the GA-BPNN model is less than 8.1% and the BPNN model is less than 12%,
 389 while overall, the E_{MR} of the GA-BPNN model is better than that of the BPNN model.

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

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

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

410
411 In summary, the calculation results prove that it is feasible to use GA-BPNNs to
412 predict the flexural capacity of post-fire RC beams.

413
414 **Fig. 6-13**
415

416 **Table 3**
417 **Table 4**

418 **6. Conclusion**

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

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

426 (2) The GA-BPNN prediction model proposed in this paper for calculating the
427 flexural capacity of post-fire RC beams combines the nonlinear mapping capability of
428 ANNs and the global search capability of GA. The predicted values of the GA-BPNN
429 model fit well with the target values. The E_{MR} of the predicted values of the NN and the

430 target values are always less than 8.1% and less than that of the BPNN, the R^2 of the
431 training samples and the test samples are 0.99526 and 0.99886, respectively,
432 indicating that the GA-BP prediction model has higher robustness and fitting ability.

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

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

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

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458 **Authors’ contributions**

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

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468 **Availability of data and materials**

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

471 They are:

- 472 Training data for machine learning
- 473 Prediction result data for machine learning
- 474 Code for machine learning

475 .

476 **Competing interests**

477 The authors declare that they have no competing interests.

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601
602
603 **Table**

604 **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_v (MPa)	c (mm)	$Target$ (kNm)	$GA-BP-simu$ (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
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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

608 $Target$ and $GA-BP-simu$ are the target value and predicted value of the reinforced
609 concrete strength, respectively; $e=|Target - GA-BP-simu| / Target$

610

611

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

612

613

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

614

615

List of Figure captions

616

617

Fig. 1 Reduction variations in the compressive strength of concrete and the yield strength of reinforcing steel

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620

Fig. 2 Procedure for the calculation of the post-fire flexural capacity

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622

Fig. 3 Beam reinforcement of specimen L5 and L9

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Fig. 4 Framework of GA-BP neural network algorithm

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Fig. 5 Architecture of the ANN

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Fig. 6 Average fitness curve with evolutionary generations

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Fig. 7 Comparison of the predicted values of BPNN and GA-BPNN

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Fig. 8 Comparison of the absolute error values predicted by BPNN and

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GA-BPNN

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Fig. 9 Comparison of the E_{MR} values predicted by BPNN and GA-BPNN

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Fig. 10 Prediction performance of GA-BPNN of training samples

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Fig. 11 Prediction performance of GA-BPNN of all samples

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Fig. 12 Prediction performance of GA-BPNN of testing samples

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643

Fig. 13 Prediction performance of BPNN of testing samples

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