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Research paper

Time-varying probability model of the reduction in bending capacity of RC beams due to corrosion of steel bars

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Abstract: Due to the reduction in bending capacity of RC beams being affected by multiple stochastic uncertainties, employing a deterministic function model to study the bending capacity of RC beams often leads to analysis errors that are difficult to accept. This paper, by analyzing the significant discrepancies between calculated values derived from computational models and results obtained from experiments, adopts a model bias coefficient to describe the uncertainty of the computational model. Building on the consideration of parameter and model uncertainties, this paper establishes a Bayesian neural network model for predicting the bending load capacity of RC beams due to reinforcement corrosion. The model is compared with the traditional Back Propagation (BP) neural networks and the Genetic Algorithm-optimized BP (GA-BP) neural networks. The results indicate that the Bayesian neural network model has the least number of iterations and the highest efficiency, with comparable average prediction accuracy to the commonly used GA-BP neural network model. It improves the accuracy by 7.44% compared to the traditional BP neural network model. Finally, based on case studies, the time-variant probability distribution of the bending carrying capacity of corroded RC beams for a service life of 100 years is obtained. It is concluded that the time-variant probability model of the resistance of corroded RC beams follows a log-normal distribution, and the established Bayesian neural network model for predicting the time-variant resistance of corroded RC beams yields better results.

Keywords: Bayesian neural network, corrosion, flexural bearing capacity, model uncertainty coefficient, reinforced concrete beam

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1. Introduction

Research on the reduction in bending capacity of reinforced concrete (RC) beam has always been a focal point in the field of civil engineering. In the preliminary stage of the research, Domestic and foreign scholars almost all adopted deterministic function model methods to analyze the resistance degradation process. Stewart et al. [1] adopted the structural deterioration reliability model to study the trend of the bending strength reliability of reinforced concrete continuous slab bridge. Ellingwood [2] studied the resistance degradation process of civil infrastructure through quantitative data. However, since the resistance degradation is affected by multiple random uncertainties, if deterministic function models are used to study the structural resistance degradation, the resulting analysis errors are often unacceptable [3].

To better investigate the randomness of structural parameters and the time-variability of resistance in the resistance degradation process, domestic and foreign scholars have constructed a variety of resistance degradation models in recent years, including probability prediction models and neural network models. Yu et al. [4], targeting the defects of traditional deterministic models and taking into account the influence of both subjective and objective uncertainties, combined with Bayesian theory, established the probabilistic model for calculating the shear bearing capacity of corroded RC beams. Šomodíková et al. [5] proposed a probabilistic determination method to evaluate the load-bearing capacity and reliability of bridges over time by combining the Monte Carlo simulation method with the nonlinear finite element calculation model. Used the Monte Carlo simulation method combined with the nonlinear finite element calculation model to evaluate the load-bearing capacity and reliability of bridges over time with a probabilistic determination method. Liu et al. [6] established a method for assessing the remaining load-bearing capacity of bridges over time, which considered non-stationary bridge load effects caused by material degradation due to increasing traffic loads and random structural deterioration.

In the field of structural engineering, despite the widespread application of probabilistic prediction and neural network-based resistance degradation models, there are still significant issues such as the cumbersome iteration of model formulas, poor generality in model computations, the neural network's limited consideration of influencing parameters, and the tendency of BP networks to fall into local optima. Furthermore, stochastic resistance degradation models for corroded Reinforced Concrete beams that account for both variable uncertainty and model uncertainty are exceedingly rare. Therefore, there is an urgent need for an accurate and straightforward method for predicting the bending capacity of corroded RC beams.

Compared to existing neural network approaches, Bayesian neural networks introduce uncertainty into the neural network, specifically by dealing with the uncertainty of network weights through regularization techniques [7]. Not only do they possess a high adaptability and powerful data mining capabilities, but they also address the problems of traditional BP neural networks, such as getting trapped in local minima, slow convergence rates, and poor generalization ability. Chen et al. [8] utilized the unique self-learning capability and strong generalization ability of Bayesian neural networks to predict the remaining service life of concrete under tensile fatigue. However, the application of Bayesian neural networks that consider both variable uncertainty and model uncertainty in the establishment of resistance degradation models for corroded RC beam structures is still rarely reported. Juan et al. [9]

employed a physically-guided Bayesian neural network, integrating approximate Bayesian computation training with a physics-based model, to provide a novel and useful tool for the rapid assessment of the load-bearing capacity of critical buildings post-earthquake.

In response to the issues present in the aforementioned studies, this paper aims to establish a time-variant probability model for the flexural bearing capacity of corroded Reinforced Concrete (RC) beams based on Bayesian neural networks, taking into account various uncertainties that occur during the actual corrosion process of RC beams. Initially, the model considers the corrosion of steel reinforcements to derive a degradation model for the flexural bearing capacity of corroded RC beams. Subsequently, it analyzes the model uncertainty inherent in existing prediction models, establishes a time-variant probability model for the bearing capacity of corroded RC beams, and develops a time-variant prediction model using Bayesian neural networks, which is then compared and analyzed with traditional Back Propagation (BP) neural networks and Genetic Algorithm-optimized BP (GA-BP) neural networks. Finally, the probability prediction model presented in this paper is validated using experimental data from 38 corroded RC simply supported beams, and the time-variant probability distribution of the flexural bearing capacity for corroded RC beams within a service life of 100 years is determined based on relevant cases, providing a reference for engineering safety assessments.

2. Deterministic model for calculating the flexural load capacity of corroded RC beams

2.1. Performance degradation model for corroded RC beams

2.1.1. Residual cross-sectional area of reinforced steel after corrosion

The primary cause of performance degradation in reinforced concrete structures is steel reinforcement corrosion, which results in a reduction of the cross-sectional area of the steel. The extent of this reduction is characterized by a time-related reinforcement cross-sectional area loss rate η:

$$S(t) = (1 - \eta(t))S_0 \tag{2.1}$$

where: $S(t)$ – denotes the cross-sectional area of reinforced steel after corrosion, S_0 – represents the initial cross-sectional area of reinforced steel.

2.1.2. Post-corrosion steel reinforcement yield strength degradation model

As the loss rate of the steel reinforcement cross-sectional area accumulates, the mechanical properties of the rebar undergo a fundamental transition from ductility to brittleness, with severe degradation in yield strength [10]. The modeling of the decline in steel reinforcement yield strength is as follows:

$$f_y(t) = (1 - k_1\eta(t))f_{y0} \tag{2.2}$$

where: k_1 – the empirical coefficient, $f_y(t)$ – represents the yield strength of the corroded reinforcement, f_{y0} – represents the yield strength of the reinforcement before corrosion.

2.1.3. Post-corrosion reinforcement and concrete bond strength degradation

The good bond between reinforcement and concrete is a prerequisite for the proper functioning of reinforced concrete structures. In existing research both domestically and internationally, scholars have reached a qualitative consensus on the rule of corrosion affecting cohesive performance. They often use the collaboration coefficient between reinforcement and concrete to reflect the impact of bond strength degradation on structural components. However the bond strength is related to many factors, such as the diameter and surface shape of the steel reinforcement, as well as the anchorage length. Since this paper mainly considers the decrease in the load-bearing capacity of RC beams due to steel corrosion, it only considers the impact of steel corrosion on bond strength. Therefore, this paper applies theBODY expression of the collaborative working coefficient between corroded reinforcement and concrete, summarized by Ma [11], to the calculation of the structures resistance of corroded RC beams.

$$k_2 = \begin{cases} 1 & \eta(t) < 1.2\% \\ 1.0168 - 0.014\eta(t) & 1.2\% \leq \eta(t) < 6\% \\ 0.72 + 0.295e^{-0.0651\eta(t)} & 6\% \leq \eta(t) < 20\% \\ 0.8 & \eta \geq 20\% \end{cases} \tag{2.3}$$

where: $\eta(t)$ – denotes the coefficient of corrosion, k_2 – represents the collaborative coefficient between the corroded reinforcement and concrete.

2.1.4. Corrosion-Induced bending capacity degradation model for RCBODY beams

Based on the aforementioned computational theory model, assuming the RC beam has a solid concrete rectangular cross-section, the calculation model for the flexural bearing capacity of a corroded RC beam is constructed as follows:

$$M(t) = k_2 f_y(t) S(t) \left[h_0 - \frac{f_y(t) S(t)}{2 f_c b} \right] \tag{2.4}$$

where: $M(t)$ – represents the bending bearing capacity of the reinforced concrete beam normal section, k_2 – represents the coefficient of synergy between corroded reinforcement and concrete, h_0 – represents the effective height of the RC beams cross-section, f_c – denotes the compressive strength of the concrete, b – is the width of the cross-section.

As can be deduced from the above equation, the flexural bearing capacity M of a corroded reinforced concrete RC beam is composed of a series of factors including material strength, cross-sectional dimensions, etc. Therefore, when analyzing the probabilistic characteristics of M, the random variability of these factors should be considered.

2.2. Limitations of deterministic flexural load capacity models

Based on the 200 sets of experimental data on the bending load capacity of corroded RC beams taken from [12], the accuracy of the corrosion RC beam flexural load capacity calculation model proposed in (2.4) is verified. The experimental information can be found in

Table 1, and the comparison between the model calculated values (denoted as M_j) and the experimental test values (denoted as M_s) is displayed in Fig. 1. Difference between calculated and tested flexural capacity and Fig. 2.

Table 1. Test beams geometrical data

Reference	**Test beams length (mm)**	**Width (mm)**	**Height (mm)**	**Thickness of protective layer (mm)**	**Tension bars**	**Concrete strength**
[12]	1700	120	200	25	2×A14	C30
[13]	1500	150	200	25	2×B16, 2×D16	25.9 MPa, 35.6 MPa
[14]	2400	200	300	30	2×A18+1×A12, 2×A20+1×A12	C30
[15]	1800	150	240	25, 30, 35	2×A22	C25
[16]	2400	240	300	25, 30, 35	2×A18, 2×A20, 2×A22	34.55 MPa
[17]	1500	150	200	14	2×A16 (Stainless steel reinforcement 2204)	C55
[18]	1800	160	250	30	3×B16	C30
[19]	900, 3000, 1800	150, 152	150, 254, 200	30	2×B10, 2×B12, 2×B14, 2×B16	[22.13-49.04] MPa
[20]	/	120	200	25, 30, 35	2×A12, 2×A14, 2×A16, 2×A18	[21.01-30.03] MPa,
[21]	1200	150	200	30	/	25.93 MPa, 35.55 MPa
[22]	2600	160	320	25	2×B20	49.8 MPa

As shown in Fig. 1 and Fig. 2, there is a significant deviation between the model calculated values and the experimental values. Although the flexural load capacity model defined by (2.4) takes into account the degradation effects of reinforcement corrosion on the yield strength f_y, the effective cross-sectional area S, and the bond strength between reinforcement and concrete k_2, thereby having a relatively solid theoretical foundation, this model is deterministic. It fails to consider the uncertainties introduced by the experimental environment, as well as the objective

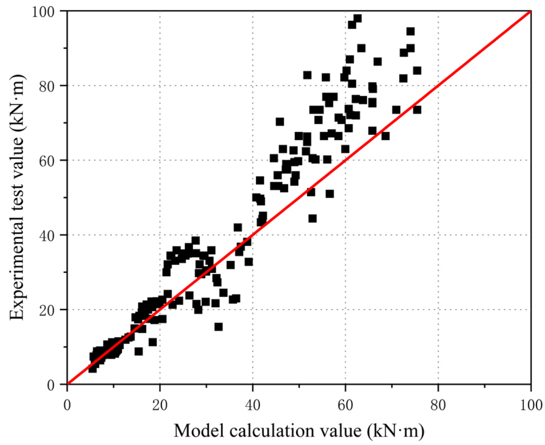

Fig. 1. Difference between calculated and tested flexural capacity

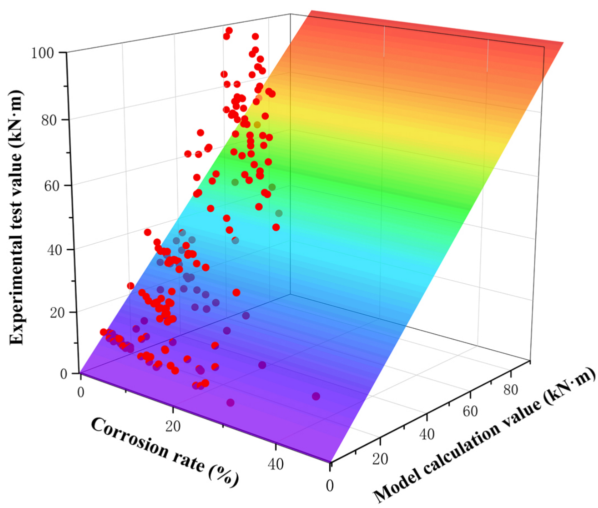

Fig. 2. The relationship between model bias and corrosion rate

uncertainties related to the geometric dimensions of RC beams, material characteristics, boundary conditions, among other factors. Additionally, subjective uncertainties arising from incomplete consideration of factors or inappropriate choice of function forms during the model derivation process also affect the results, leading to a certain degree of dispersion in the calculation outcomes and an inability to describe the probability distribution characteristics of the bending load capacity of corroded RC beams. Therefore, it is necessary to build a predictive model for calculating the bending load capacity of corroded RC beams on the basis of the deterministic model described in (2.4), by comprehensively considering the effects of both objective and subjective uncertainties.

3. Bayesian neural network time-variant prediction model for flexural bearing capacity of corroded RC beams

3.1. Uncertainty of the prediction model

Considering the limitations of the aforementioned deterministic flexural bearing capacity model, in order to represent the objective uncertainty present in factors such as the geometric dimensions of RC beams, material properties, and boundary conditions, as well as the subjective uncertainty arising during the model derivation process due to incomplete consideration of factors or improper selection of functional forms, and the model uncertainty introduced by environmental changes when indoor experiments simulate actual field conditions, this paper intends to use a model bias coefficient, defined as the ratio between experimental values and calculated values.

$$M_s = \varepsilon M_j \tag{3.1}$$

where: M_s – represents the experimental values of the bearing capacity of the corroded reinforced concrete beam, M_j – represents the calculated values of the bearing capacity of the corroded reinforced concrete beam, ε – is the model bias coefficient, which represents a multivariable function of factors such as the geometric dimensions of an RC beam, material properties, and corrosion conditions.

From the above, a calculation model for the flexural bearing capacity of corroded RC beams that considers uncertainty can be obtained, as shown in the following (3.2).

$$M(t) = \varepsilon k_2 f_y(t) S(t) \left[h_0 - \frac{f_y(t) S(t)}{2 f_c b} \right] \tag{3.2}$$

3.2. Determination and preprocessing of neural network data samples

To predict the bending bearing capacity of RC beams after corrosion, based on the analysis of various parameters in (3.2), this paper selects 9 variables for the input layer, which include the model calculation value (M_j), the initial yield strength of the reinforcement (f_{y0}), the initial cross-sectional area of the reinforcement (S_0), the compressive strength of the concrete (f_c), the thickness of the concrete protective layer (C), the diameter of the reinforcement (D), the height of the RC beam section (h), the width of the RC beam section (b), and the corrosion rate (η); the output layer result is set to be the model bias coefficient (ε). Based on the experimental data of the bending bearing capacity of 200 corroded RC beams [12], the sample data consisting of input and output are divided into a training set and a test set in a 7:3 ratio. To meet the training requirements of the neural network model, this paper uses the mapminmax function to normalize the data to [0–1] to avoid affecting the accuracy of subsequent simulation predictions.

3.3. Setting parameters for Bayesian neural networks

To better demonstrate the feasibility and effectiveness of the Bayesian Neural Network time-variant prediction model in predicting the bending bearing capacity of corroded RC beams, this paper compares it with the traditional BP neural network prediction model and the GA-BP neural network prediction model.

3.3.1. Determination of hidden layer structure and neuron quantity

The hidden layer is the hierarchical structure between the input and output of the BP neural network, and the learning mapping ability of the BP neural network can be enhanced by changing the number of layers in the hidden layer. Furthermore, the number of neurons in the hidden layer is another key point in determining the structure of the BP neural network, but currently, there is no unified formula to determine the value. Too many or too few neurons can ultimately affect the simulation prediction accuracy of the neural network. Due to the small dataset in this paper, a random algorithm is used to obtain the optimal number of hidden layers and neurons. The number of layers in the hidden layer is chosen to range from [1–3], and the number of neurons in the hidden layer is chosen to range from [5–29]. The loss value uses mean square error, which is calculated as (3.3). After a series of error comparisons, the optimal parameters are determined to be when the mean square error is 0.0126, with two hidden layers, respectively containing 17 and 9 neurons.

$$MSE = \frac{1}{N} \sum_{n=1}^{N} \left(\hat{Y}(n) - Y(n) \right)^2 \tag{3.3}$$

where: $\hat{Y}$(n) – denotes the actual value of the sample, $Y(n)$ – represents the predicted value of the neural network, N – is the number of the dataset.

At the same time, the same hidden layer structure is used to train the Bayesian neural network, obtaining the loss value of 0.0046, which meets the requirements for optimal network parameters.

3.3.2. Selection of learning rate

The key to adjusting neural network weights and thresholds lies in determining the learning rate. This paper uses k-fold cross-validation ($k = 5$) to determine the learning rate [23]. The specific method is to divide the sample dataset into the training set and the test set at a ratio of 7:3, and then divide the training set into 5 cross-validation groups, taking each group in turn as a validation set and the remaining four groups as a training set. The learning rate is optimized according to the loss function results on the validation set. Fig. 3 shows the changes in the loss values of the BP neural network on the validation set when the learning rates are set to 0.01, 0.005, 0.001, 0.0005, and 0.0001.

As can be seen from Fig. 3, as the number of training increases, the value of the loss function decreases significantly, which indicates that the BP neural network can learn the mapping relationship between the parameters of the corroded RC beam carrying capacity degradation model and the bending bearing capacity well. However, when the learning rate is set at 0.01, 0.005, 0.001, and 0.0005, not only does the loss function value decrease too quickly, but there is also the possibility of falling into local optima or saddle points during training. Therefore, this paper selects the relatively good descent rate of 0.0001 as the appropriate learning rate. Fig. 4 shows the loss function of the Bayesian neural network on 5 validation sets when the learning rate is set to 0.0001.

In the actual modeling process, the Bayesian neural network is built using MATLAB 2022a, and the model parameters are shown in Table 2. Model setup To ensure the accuracy of the experiment and the comparability of the results, a traditional BP neural network with the same

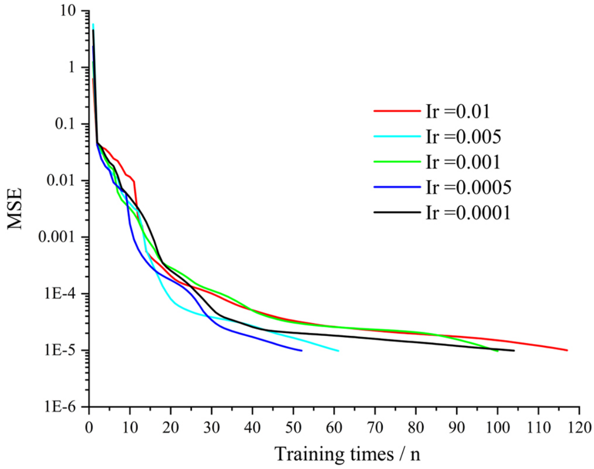

Fig. 3. The effect of learning rate

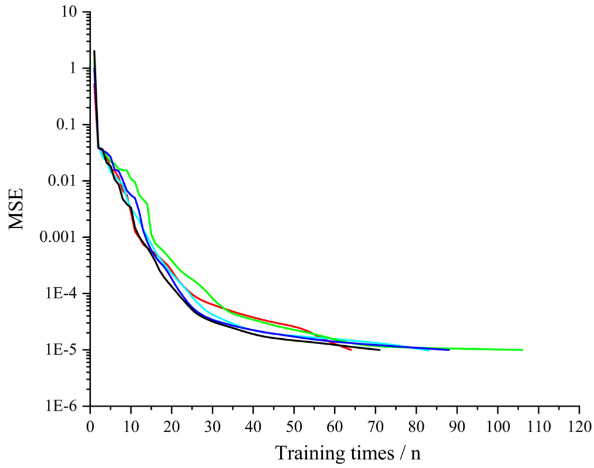

Fig. 4. The loss value of Bayesian neural network when the learning rate is 0.0001

structure and a GA-optimized BP neural network are trained. The parameters of the genetic algorithm are shown in Table, which considers the corrosion characteristics of reinforced concrete beams and the simulation process.

3.4. Model prediction results and validation

The neural network, once trained, exhibits good generalization ability. The paper validates the proposed Bayesian neural network prediction model based on the flexural bearing capacity data of 38 corroded RC samples from [24]. The comparison results are shown in Fig. 5

Table 2. Model setup

Loss function	Optimization algorithms	The number of hidden layers	Hidden layer dimension	Learning rate	Maximum number of sessions	Target accuracy
MSE	Trainbr	2	17,9	0.0001	10000	0.00001

Table 3. Genetic algorithm parameters

Optimization algorithms	Learning rate	Target accuracy	Population size	The number of iterations	Crossover probability	Mutation probability
Traingdx	0.0001	0.00001	50	200	0.6	0.2

as follows. As shown in Fig. 5, the Bayesian Neural Network predicts the flexural bearing capacity of corroded RC beams more accurately than the BP Neural Network. It is comparable to the currently more practical GA-BP Neural Network prediction accuracy. The prediction accuracy R^2 of Bayesian Neural Network model is 0.904, the prediction accuracy R^2 of GA-BP Neural Network model is 0.885, while the BP Neural Network model has a prediction accuracy R of 0.465.

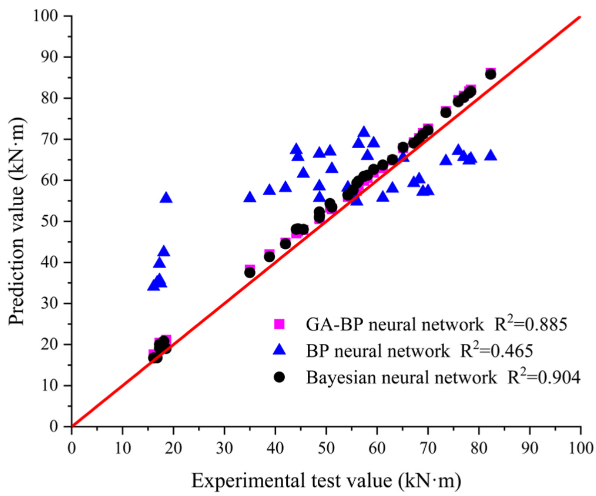

Fig. 5. Model Accuracy Validation

To avoid the randomness of high precision in single neural network predictions, this paper conducted a total of 200 predictions based on the basic parameters listed in the Tab. 1 and Tab. 2, and the precision of the prediction results is depicted in Fig. 6. The prediction accuracy is expressed by the correlation coefficient R^2.

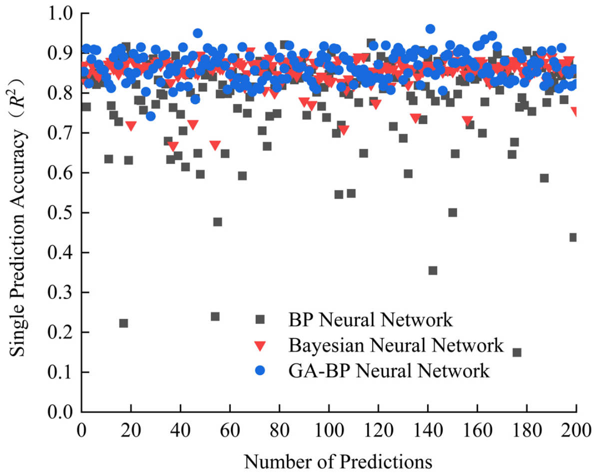

Fig. 6. Comparative analysis of prediction accuracy

From Fig. 6, it can be observed that the predictions of the bending bearing capacity of the corroded RC beams by the trained Bayesian neural network are more stable than those of the BP neural network and the predictive performance is close to the more practical GA-BP neural network currently in use. The average prediction accuracy of the Bayesian neural network is 85.44%, which is 7.44% higher than that of the BP neural network, thereby indicating a strong correlation between the Bayesian neural network predictions and the experimental data.

4. Case analysis

Statistical data shown in Table 4 are used, which include domestic and international statistics on the yield strength of corroded rebars f_{y0}, concrete compressive strength f_c, concrete cover thickness C, and initial rebar diameter D.

Table 4. Statistics of input layer variables

Variable	Distribution type	Mean	Variation Coefficient	References
Initial yield strength of the rebar f_{y0} (MPa)	normal distribution	<380,412.3,528.43>	<0.098,0.114,0.024>	[25]
concrete compressive strength f_c (MPa)	normal distribution	<27.9,34.19,20.72>	<0.17,0.027,0.177>	[26]
concrete cover thickness C (mm)	normal distribution	<20,25,30,35>	0.05	[26]
initial rebar diameter D (mm)	normal distribution	<14,16,18,20,22>	0.03	[26]

The initial cross-sectional area S_0 of the rebar is calculated with the diameter D, while the section height h, section width b, and the rebar cross-sectional area loss rate η are determined based on existing literature and experimental experience, with the parameter limits set as follows: h ranges from [150, 300], b ranges from [100, 200], and the η is taken from the range [0, 80] as per Ma et al. [29] for reliability and lifespan assessment of RC bridges under multi-source uncertainty information. Based on the aforementioned parameters distribution, Latin Hypercube Sampling is used to sample 10000 times, and each input layer variable sample is calculated. To obtain the mean and standard deviation of the probability distribution of the flexural bearing capacity of corroded RC beams at different times, the trained Bayesian Neural Network is used for multiple predictions. The mean and standard deviation coefficients are calculated by dividing the prediction results by the initial flexural bearing capacity. The corresponding resistance probability distribution curve is shown in Fig. 7. It is evident from the figure that the log-normal distribution fits well, hence it can be inferred that the bending bearing capacity M follows a log-normal distribution. This provides a theoretical basis for the safety and durability assessment of corroded RC structures.

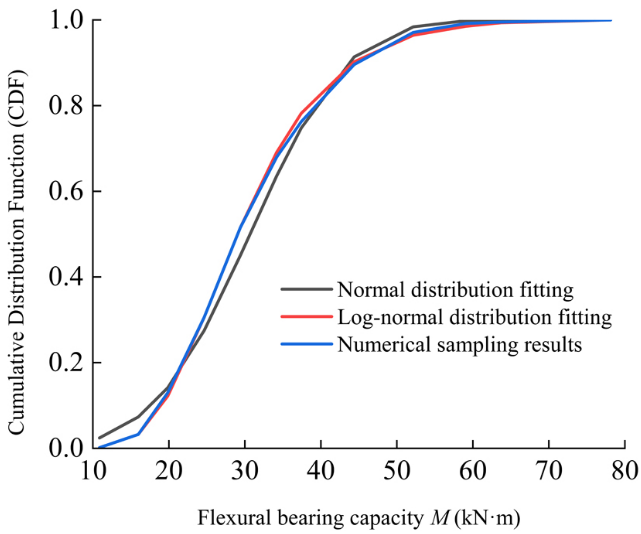

Fig. 7. Fitting of probabilistic models of resistance

As can be seen from Fig. 8, after the initial corrosion time of 18 years, as the reinforcement corrosion accumulates over time, the mean of the beam's bending bearing capacity significantly decreases. At the same time, the coefficient of standard deviation of bending bearing capacity also shows a stable growth over time. This indicates that closer to the end of service life, the fluctuation range of the component's resistance becomes larger, which means that the beam is very likely to fail towards the end of its service life and should therefore be monitored for safety.

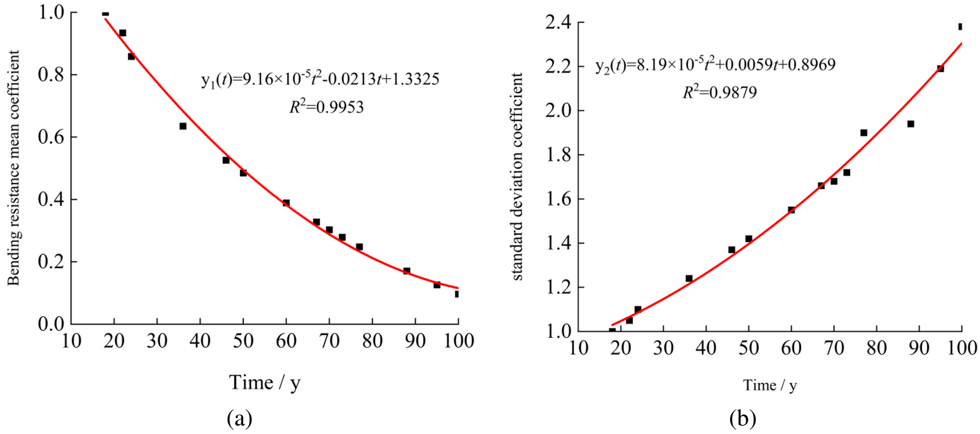

Fig. 8. Time-varying curve of mean and standard deviation coefficient: (a) Mean coefficient; (b) Standard deviation coefficient

5. Conclusions

1. By studying the actual macroscopic resistance deterioration characteristics of reinforced concrete beams, the impact of model uncertainty on resistance prediction results was analyzed, resulting in a probabilistic model for the bending bearing capacity of corroded RC beams that conforms to a log-normal distribution. Based on this, a time-varying predictive model of the bending bearing capacity of corroded RC beams was constructed using Bayesian neural networks.
2. Compared to the traditional BP neural network in this paper, which requires hundreds of iterations to converge, and the GA-BP neural network, which takes a long time to converge, the time-varying predictive model of the bending bearing capacity of corroded RC beams based on the Bayesian neural network converges in just a few dozen iterations. It is the most efficient and results in high prediction accuracy. The ratio of experimental values to predicted values has a mean of 0.96 and a variance of 0.175, providing a low-cost and efficient method for evaluating the bending bearing capacity of corroded RC beams.
3. Steel reinforcement corrosion plays a dominant role in the deterioration process of the bending bearing capacity of beam components. Based on the probability model assumed in this paper, by the end of the service period (the 100th year), the bending bearing capacity of corroded RC beams is only 9% of the initial value, hence special attention should be paid to the safety condition of corroded beam components in the final years of service life.

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