A prediction model for the seismic intensity in meizoseismal area based on Genetic Neural Network

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Abstract. In this paper, a novel model for seismic intensity prediction in meizoseismal area is proposed based on BP neural network. 322 earthquake events of M5.0 or more occurred in the mainland of China from 1966 to 2017 with detailed intensity records. From the collected data set, seven factors related to the seismic intensity are selected. Principal component analysis is performed on these factors to generate the network input, while the intensity of the epicenter is the output of the network. The BP neural network is optimized by using genetic algorithm. Simulation results show that, compared to the traditional prediction methods, the proposed prediction model based on BP neural network has obvious advantages in terms of prediction accuracy and correct prediction probability.

1. Introduction
There are many factors that affect the distribution of seismic intensity, such as magnitude, focal depth, site conditions, intensity evaluation criteria. The mapping between these factors and the intensity is quite complicated. In traditional models [1-5], only the magnitude and focal depth are considered, which can hardly accurately describe the intensity distribution of an earthquake. In the long-term work experience, it has been found that the seismic intensity distribution calculated by the traditional intensity attenuation model is quite different from the actual situation [6-8]. With the rapid development of artificial intelligence, artificial neural network has been widely used in the field of earthquake disaster prediction [9-13]. However, no one had established multi index prediction model of the intensity in meizoseismal area based on artificial neural network. By exploiting a large number of historical data, we carefully pick out 7 factors which affect the seismic intensity, and propose a novel model to predict the intensity in meizoseismal area by utilizing BP neural network. To construct the network input, we extract the principal component of the selected factors and the BP neural network is optimized by genetic algorithm, so that a rapid prediction of the intensity in meizoseismal area can be established after an earthquake, which provides an important basis for the emergency decision-making after an earthquake.

2. Data and principal component analysis

2.1. The data
In this study, 322 historical earthquakes with M5.0 or more and detailed intensity records from the mainland of China were collected from 1966 to 2017. Through analyzing the data, we select seven factors related to seismic intensity, which are magnitude, focal depth, continental division (the mainland of China was divided into eastern and western regions with 105 °E as the boundary, represented by numbers 1 and 2 in the parameters); $V_s30$ (equivalent shear wave velocity in the depth range of 30m
below the surface). PGA (design peak acceleration), GDP per capita and corresponding version of intensity table (1957s, 1980s, 1999s and 2008s, represented by numbers 1~4 in the parameters). The details can be found in Table 1.

| Magnitude | Depth | Continental division | $V_{S30}$ (m/s) | Design PGA/g | GDP | Intensity table | Intensity |
|-----------|-------|----------------------|----------------|--------------|-----|-----------------|----------|
| 5.2       | 10    | 2                    | 731            | 0.15         | 3.45| 1               | 6        |
| 5.3       | 8     | 1                    | 530            | 0.10         | 6.37| 1               | 6        |
| 5.9       | 25    | 2                    | 611            | 0.40         | 3.93| 1               | 6        |
| 5.6       | 30    | 2                    | 900            | 0.30         | 3.93| 1               | 7        |
| 6.9       | 10    | 2                    | 900            | 0.30         | 3.93| 2               | 8        |
| 5.0       | 21    | 2                    | 835            | 0.30         | 4.47| 2               | 6        |
| 6.3       | 18    | 2                    | 900            | 0.30         | 4.47| 2               | 8        |
| 5.1       | 10    | 2                    | 900            | 0.20         | 3.93| 4               | 7        |
| 5.5       | 7     | 1                    | 900            | 0.05         | 3.80| 4               | 7        |
| 5.4       | 10    | 1                    | 900            | 0.05         | 4.20| 4               | 7        |

2.2. Principal component analysis

Usually, in order to fully describe the research problem, we will collect as many relevant indicators as possible. However, too many indicators may bring overlap and cover up some important information. Therefore, the selected indicators should be selected reasonably to ensure the sensitivity, representativeness and conciseness of the original information. The basic idea of principal component analysis is to transform multiple indexes into several comprehensive indexes (i.e. principal components) through dimensionality reduction. Each principal component can reflect most of the information of the original variables, and the information contained is not repeated with each other, which simplifies the problem and makes the results more scientific and effective.

Let $n$ be the number of samples, $m$ be the number of indicators corresponding to each sample, $x_{ij}$ is the $j$th observation value of the $i$th sample, expressed as $X = [x_{ij}]$. We normalize the matrix and calculate the correlation coefficient among these indicators as well as characteristic value $\lambda_j$, the contribution rate of each principal component can be written as

$$\lambda_j / \sum_{j=1}^{m} \lambda_j (j = 1,2, ..., m)$$

Cumulative contribution rate is:

$$\sum_{j=1}^{j} \lambda_j / \sum_{j=1}^{m} \lambda_j (j = 1,2, ..., m)$$

In summary, we first perform the principal component analysis after normalizing the sample data, then the index corresponding to the characteristic value $\lambda_j$ whose cumulative contribution rate reaches $85\% \sim 95\%$ is selected as the principal component. Finally, we find out that the first 6 principal components can replace the original 7 factors’ characteristic attributes, so we choose the first 6 components as the principal component characteristic attributes to judge the intensity in meizoseismal area. Multiply the normalized sample data with the corresponding load matrix to get a new array, which will be used as the input of BP neural network model.

3. Neural network model

3.1. BP Neural network
BP neural network (back propagation network) is a multilayer feedforward neural network. The main feature of the network is that the signal is transmitted forward and the error is transmitted backward. If the expected value cannot be achieved at the network output layer, the prediction error, which is the difference between the actual value and the network output, will be back propagated, and the weights and threshold value of the network will be adjusted according to the prediction error. In this way, the output of the network will converge to the expected value finally. Based on the results of principal component analysis and the prediction target, the BP neural network in this paper is designed to have three layers, and the number of neurons in the input layer, the hidden layer and the output layer are respectively 6, 12, and 1. Tansig, purelin and trainlm functions are selected as input layer transfer function, hidden layer transfer function and training function, respectively; the learning rate of network training is set as 0.1, the target accuracy is set as 0.01, and the maximum number of iterations per time is set to be 1000.

3.2. Optimization of network by genetic algorithm

Due to the error back-propagation characteristics of BP neural network, the network has a high dependence on the initial weights and threshold value. However, the initial values are given randomly when initializing the network, which easily causes the algorithm to fall into the local optimal solution, and results in low prediction accuracy and poor generalization ability of the model. In order to avoid the above defects, before the establishment of the model, genetic algorithm is used to optimize the BP neural network: after binary coding of the initial weights and thresholds of the network, we take the overall error of the network training as the fitness function. After multiple genetic operations have been carried out, the individual with the highest fitness value is selected as the genetic result, the initial weights and thresholds of the neural network are reassigned. This process will be carried out iteratively until the pre-set conditions are met.

3.3. Network training and modeling

We randomly divided the sample data into three parts: training sample set, test sample set, and validation sample set, each sample set occupies 60%, 20%, and 20% respectively. The training samples are used to participate in machine learning to improve training accuracy; the test samples are used to evaluate the prediction accuracy of the network; the verification samples are used to prevent the network from overfitting. We set that when the training error of the verification sample does not decrease for 15 consecutive times, the training is terminated, and the minimum value of the accuracy of the verification sample is determined as the best accuracy, and the training result corresponding to this accuracy is an ideal model. The training process is shown in Figure 1. As can be seen from Figure 1, at the 8th iteration the verification sample error reaches a minimum, and then it continues to increase. In the next iteration, the training error continues to decrease, but the error of the test samples show an upward trend, which indicates that the network begins to enter an overfitting state, so we choose the result of the 8th iteration training as the final neural network model.

![Figure 1. The error curve of three kinds of samples](image-url)
4. Model evaluation

We have collected the other three types of intensity attenuation models currently widely used in China's earthquake research department: the eastern and western subregional intensity attenuation models (Model 1), the fifth-generation zoning map intensity attenuation models (Model 2), and the regional intensity attenuation models of different regions in China given by different scholars (Model 3). Based on all of the sample data, simulations are performed by using the above three models and our neural network model. The prediction errors of these four models are evaluated, and their distributions are shown in Figure 2. It can be seen from Figure 2 that the simulation error distribution of the neural network model is better than the other three models. The errors of the proposed model are evenly and concentratedly distributed on both sides of the zero value, and the prediction error distributions of the other three models are more discrete in terms of MSE.

![Figure 2. Prediction error distribution of four models](image)

Figure 3 shows the time distribution of the simulation errors of the four models. The fourth order polynomial is used to fit the error data. It can be seen from Figure 3 that the prediction errors of the other three models mostly lie above the 0 axis, which indicates that the prediction results are generally large, at the same time, the error curve fluctuates with time, but this phenomenon does not exist in neural network models.

![Figure 3. Distribution of Prediction error with time for four models](image)

(a) Neural network model  (b) Model 1  (c) Model 2  (d) Model 3. The red solid line denotes regression curve of polynomial with 4 degree.

Table 2 lists the prediction results of the four models for the intensity of the 322 earthquake events. As can be seen from the table, the accuracy of the prediction results of the neural network model is 80%, which is significantly improved compared with the other three models. Also, the other three models have obvious systematic deviations, that is, the prediction results are generally large.
Table 2. Prediction results of four models.

| Model          | Correct rate | Greater than actual | Less than actual |
|----------------|--------------|---------------------|------------------|
| Neural network model | 80%          | 11%                 | 9%               |
| Model1         | 66%          | 19%                 | 15%              |
| Model2         | 61%          | 22%                 | 17%              |
| Model3         | 62%          | 24%                 | 14%              |

5. Conclusion
In this study, seven factors closely related to the seismic intensity in meizoseismal area were selected. A multi index prediction model has been proposed by using genetic neural network. The simulation results prove that the proposed model has good stability. Compared to the traditional models, the proposed model has significantly improved the prediction accuracy and system bias of the intensity in meizoseismal area. Therefore, the proposed model based on BP neural network can provide fast and accurate intensity prediction for meizoseismal area, which is important and necessary for the emergency decision-making after earthquake.

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