Advances in Computer Science Research, volume 87
3rd International Conference on Mechatronics Engineering and Information Technology (ICMEIT 2019)

Prediction Model of Expressway Natural Risk Loss

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Abstract. Natural risks of expressway remain an important part of its operation risks. However, due to the variety, universality, locality and suddenness of natural risks, the prediction of expressway natural risks is difficult to forecast and control. In this paper, the expressway natural risk loss prediction model is established by the combining method of Chaos theory and Neural network according to the accident percentage data of rainy weather in recent 20 years in Shandong province. The use of this combining method can solve the problem of uncertain risk factors in expressway operation risks and can provide for decision-making reference and data support for expressway management and operation departments.

Keywords: Expressway; nature risk; prediction; chaos theory; neural network.

1. Introduction

Expressway occupies an extremely important position in the modern transportation system. However, due to the complexity of the expressway and the varied operating environment, its operation faces lots of risks, among which, the varied natural risks remain a great challenge for its operation process. The most important factor in natural risks is bad weather, which mainly includes rain, snow, fog, landslides, mudslides, earthquakes and so on. The impact of bad weather on the expressway operation is mainly reflected in the following aspects: (1) Affecting the road capacity and causing frequent traffic accidents. Firstly, the severe weather such as rain, snow, fog and etc. will lead to reduced visibility, reduced driving speed, and reduced road network capacity, which will cause expressway congestion and even paralysis. Secondly, poorer visibility and slippery roads can easily cause traffic accidents and heavier traffic congestion. (2) Debris flow, landslides, earthquakes and other natural disasters will cause severe damage to the expressway infrastructure, leading to huge economic losses. (3) The uses of snow melting materials and etc., will also affect the operational life of the expressway.

It can be seen from the above analysis that severe weather is a huge risk in the expressway operation. In that sense, how to reduce road traffic accidents and highway operation losses caused by severe weather has been an urgent problem to be solved. This paper analyzes the natural risks faced in the expressway operation and then establishes an expressway natural risk loss prediction model to provide reference for its management and decision-making.

2. Chaos Characteristics of Natural Risks

2.1 Chaos Theory.

Chaos theory is a method of both qualitative thinking and quantitative analysis. It is used to explore the behavior of dynamic systems that cannot rely on a single data relationship, but must be explained and predicted by the overall and continuous data relationship [1]. In previous studies, people usually think that natural risks are characterized by contingency, irregularity and suddenness. But in fact, these unexplained phenomena are just pseudo-random phenomena that appear to be random [2]. As for that, Chaos theory is the best way to solve such problems, and the scientific community has concluded that "chaos theory is the third breakthrough and revolution in the scientific world" [3].

2.2 Chaotic Characteristics of Natural Risks.

The natural risks and other disaster-related studies have showed that expressway natural risks have the obvious "chaotic characteristics" and also the following characteristics:

(1) The occurrence of natural risks has discontinuous and sporadic features, which positions a discontinuous function in time coordinates.

(2) When the natural risk occurs, the characteristic value of the risk factor deviates far from the mean value, especially when the extra-large risk occurs, and its risk factor value will be extremely out of control.

(3) Severe natural risks, such as earthquakes and heavy rains, manifest as a sudden release of environmental capacity, which usually occurs after a long period of accumulation.

The occurrence of natural risks is usually closely related to climatic conditions and human activities. It is a step-by-step process based on time series. Its occurrence can be regarded as the release process of natural forces, with obvious characteristics of “looking like random but actually not random”, that is, natural risks have significant "chaos" characteristics.

3. Prediction of Expressway Natural Risk Losses

3.1 Data Source

The data in this paper are derived from the statistics of road traffic accidents in rainy days in Shandong Province during the past 20 years. In order to better eliminate the impact of the increasing roads number and improved vehicle performance on the number of accidents, the percentage of road traffic accidents is used as the research object, and the data is shown in Table 1.

Tab.1 The Percentage of Road Accidents in Rainy Days in ShanDong Province from 1997 to 2017 (%)

Numble	Year	Percentage of the traffic accidents (%)	Numble	Year	Percentage of the traffic accidents (%)
1	1998	3.02	11	2008	4.74
2	1999	4.40	12	2009	4.57
3	2000	3.57	13	2010	4.85
4	2001	4.25	14	2011	6.23
5	2002	3.35	15	2012	3.87
6	2003	4.17	16	2013	3.82
7	2004	4.44	17	2014	5.32
8	2005	5.00	18	2015	4.51
9	2006	2.84	19	2016	4.65
10	2007	4.11	20	2017	4.33

3.2 Theory and Method

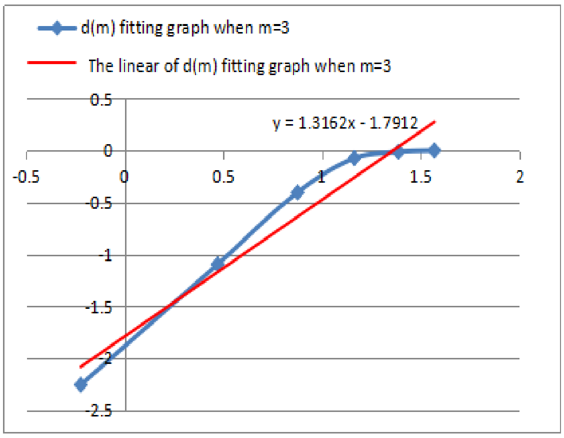
The chaotic characteristics of the unknown system time series are usually identified by numerical methods. The phase space reconstruction is used to determine the delay time, the embedding dimension m, and the neural network-based reconstruction phase space data analysis, and in such a way to determine whether the system has Chaotic at-tractors (chaotic characteristics) or not, and achieve the judgment and prediction of system regularity [4] [5].

(1) Determination of phase space delay time of natural risk time series

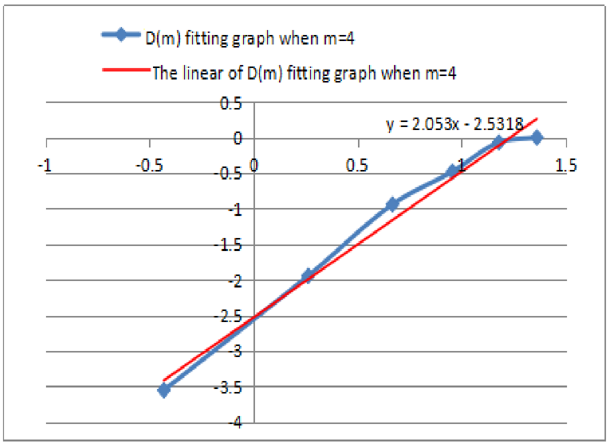
Theoretically, the delay time can be chosen arbitrarily when reconstructing one-dimensional time series without noise and infinite length [6][7]. However, in natural risk prediction, the time series contains noise and the length is limited, so the delay time needs to be re-determined. This paper uses a simple and effective auto-correlation function method (Equation 1) for analysis [8]:

$$C(\tau)=\frac{\sum_{i=1}^{n-\tau}(x(i+\tau)-\overline{x})(x(i)-\overline{x})}{\sum_{i=1}^{n-\tau}(x(i+\tau)-\overline{x})^2} \qquad (1)$$

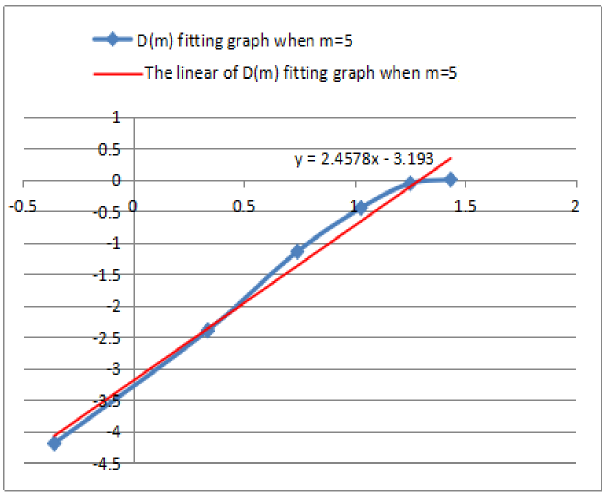
Where: x_i is the percentage of traffic accidents in the i-th year; $\overline{x}$ is the average of road traffic accidents percentage in all years; and $\mathrm{C}(\tau)$ is the value of the auto-correlation function. When $\mathrm{C}(\tau)\approx 0$, the value of the delay time τ will be the phase space delay time of the natural risk time series. After calculation, when $\tau=3$, then $\mathrm{C}(\tau)\approx 0$. Therefore, the natural risk time series phase space delay time will be determined to be 3.



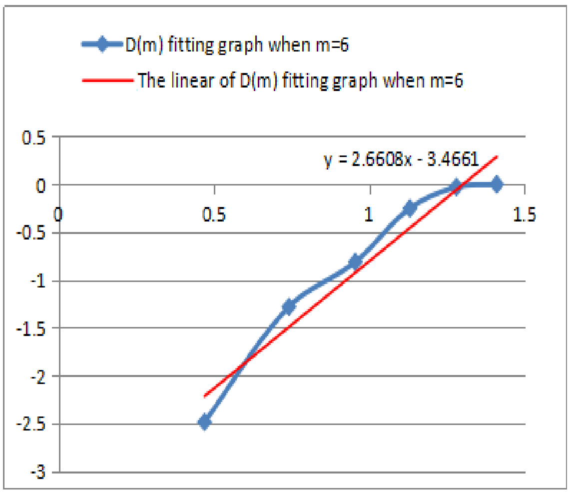
(a)when m=3,d(m)Scatter plot



(b)when m=4, d(m)Scatter plot



(c) when m=5, d(m)Scatter plot



(d)when m=6, d(m)Scatter plot

Fig. 1 Scatter plot of d(m) with different values of embedding dimension m

(1) Determination of the system embedding dimension m

The calculation of the embedding dimension m is determined by G-P method, and the specific steps are as follows [9-12]:

(1) According to the determined delay time, the study started with a smaller dimension m0 (the initial value of m0 is selected as 3 in this study), and then could obtain a new phase space y_i.

(2) Calculating the cumulative distribution function of the system through the equation $C_n(r) = \frac{1}{N(N-1)} \sum_{i \neq j}^{N} \theta(r - |X_i - X_j|)$. Where the phase point $|X_i - X_j|$ is the distance between X_i and X_j; the cumulative distribution function $C(r)$ indicates the probability that the distance between two points of the phase space at-tractor is less than r.

(3) According to equation $d_n(m) = \frac{\ln C_n(r)}{\ln r}$, the correlation dimension value $d(m_0)$ is obtained by data fitting.

(4) Increasing the value of m gradually until the value $d(m)$ does not change with the value of m, and the value at this time will be the correlation dimension.

Due to the large amount of calculation in this part, this paper uses the programming method to achieve the following scatter distribution and fitting results: The analysis and fitting results show that when m=6, $d(m) = 2.1396$, and when the value of m continues to increase, the value $d(m)$ will just change little. So, it is determined that when m=6 it will be the saturated embedding dimension, and the system will be chaotic.

3.3 Prediction of Natural Risk Loss Value of Expressway based on BP Neural Network

(1) Principle of neural network

Artificial neural network is a model built by simulating human nervous system. Because it has the ability of self-organization, self-learning and memory, and also has the advantages of distributed, parallel and high robustness, it has been widely used in recent years [13] [14]. The most commonly used BP neural network in the process of prediction and recognition is the most widely used 3-layer BP neural network. This paper chooses 3-layer BP neural network as the prediction method [15-17].

(2) Establishing a network

In the process of establishing the neural network, the embedding dimension m=6 is firstly constructed according to the determined natural risk time series of the expressway, and the first five components of the reconstructed phase space are used as the number of nodes in the network input layer, and the number of nodes in the output layer is 1 after the data entry. The resulting learning sample and expected output are as follows [18]. Learning sample input:

$$\begin{bmatrix} x(1)\cdots x(n-(m-1)\tau) \\ x(1+\tau)\cdots x(n-(m-2)\tau) \\ x(2+\tau)\cdots x(n-(m-3)\tau) \\ \cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots \\ x(1+(m-1)\tau)\cdots x(n-\tau)) \end{bmatrix}^{T}$$

Expected output:

$$\begin{bmatrix} x(1+(m-2)\tau) \\ x(2+(m-2)\tau) \\ x(3+(m-2)\tau) \\ \cdots\cdots\cdots\cdots \\ x(n) \end{bmatrix}$$

(3) Learning

After determining the input and output structure of the network, the network is trained using the percentage of natural risk rainy road accidents for nearly 20 years until the error accuracy requirements are met.

(4) Prediction

After the network training is finished, the last 5-dimensional phase space is added to the network input to achieve the prediction of the pair $x(t_n + l)$.

3.4 Prediction Results and Verification

The comparison between the fitted value and the measured value after the network learning is shown in Fig. 2. The analysis shows that the method can well predict the percentage of road traffic accidents in expressway rainy days, and the relative error of most predicted data is less than 5%. The data was validated with data from 3 years before 1998, and the results have showed that this model has high prediction accuracy.

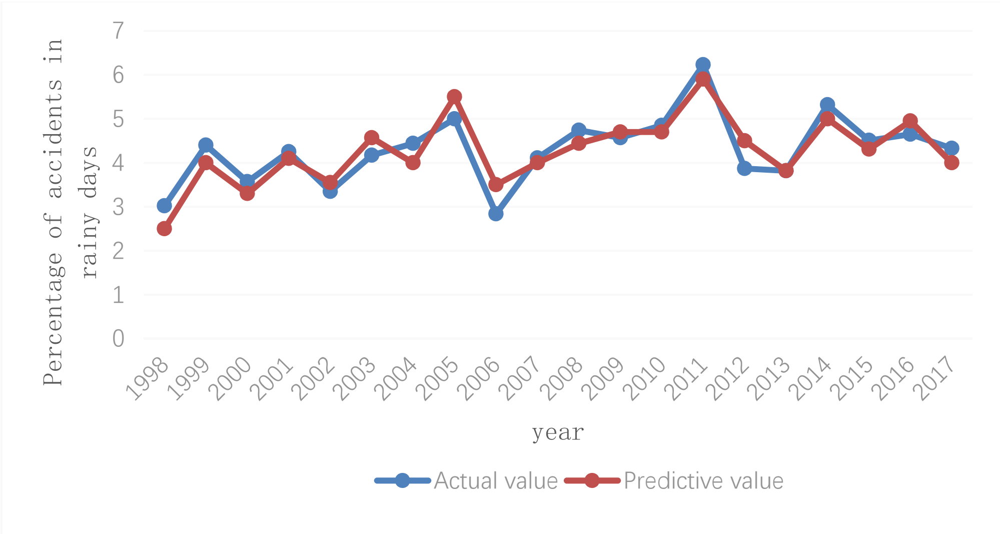


Fig.2 Comparison diagram of actual value and predicted value

4. Summary

Through the above research, the following conclusions are drawn: (1) The natural risk of expressway has chaotic characteristics, and its one-dimensional time series contains the structure of at-tractors; (2) Through the analysis and prediction of the percentage of road traffic accidents in rainy days, the expressway natural risk loss prediction model established by the combination of chaos theory and neural network has high prediction accuracy. (3) This study only analyzes the percentage of rainy days accidents, and the model predicts a large time span. Therefore, the applicable time scale needs to be further determined; (4) Whether the model is applicable to other natural risk loss predictions still needs further study.

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