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State-Based Technical Condition Assessment and Prediction of Concrete Box Girder Bridges

Zewen Zhu [1,2,3], Kuai Ye [1,2,*], Xinhua Yu [4], Zefang Lin [1,2,3], Gangzong Xu [1,2,3], Zhenyou Guo [5], Shoushan Lu [1,5], Biao Nie [5] and Huapeng Chen [5,*]

1 Jiangxi Institute of Transportation Research Co., Ltd., Nanchang 330013, China; 14115294@bjtu.edu.cn (Z.Z.); 15270475350@163.com (Z.L.); gangzongxu@163.com (G.X.); lu_shoushan@foxmail.com (S.L.)
2 Jiangxi Jiaoke Transportation Engineering Co., Ltd., Nanchang 330013, China
3 Research and Development Center on Technologies and Equipment of Long-Span Bridge Construction Ministry of Transport, Nanchang 330013, China
4 Road Network Operation Management Company, Jiangxi Provincial Communication Investment Group Co., Ltd., Nanchang 330013, China; xinhuayu89048744@163.com
5 School of Transportation Engineering, East China Jiaotong University, Nanchang 330013, China; 18289339570@163.com (Z.G.); xnniebiao@ecjtu.edu.cn (B.N.)
* Correspondence: 17770418143@163.com (K.Y.); hp.chen@ecjtu.edu.cn (H.C.)

Abstract: The technical condition of bridges has become a crucial issue for organizing the maintenance and repairs in bridge management systems. It is of great practical engineering significance to construct an effective model for predicting the technical condition degradation of the bridge through the use of the historical inspection data. Based on the semi-Markov random process, this paper proposes a useful deterioration prediction model for bridges in the highway network. From the historical inspection data of the prefabricated concrete box girder bridges, the degradation curves of technical condition rating are obtained. The effect of bridge length on degradation rate of the prefabricated concrete box girder bridges is analyzed. According to the Weibull distribution parameters of different condition grades, the technical state degradation models for a bridge group and an individual bridge are proposed to predict the performance of the overall bridge and superstructure of the bridge. The results show that with the increase in bridge length, the degradation rate of bridge technical condition increases. The degradation rate of the technical condition of the superstructure is faster than that of the overall bridge. The proposed semi-Markov stochastic degradation model for the bridge group can not only predict the different condition ratings of the bridges at any time, but also predict the future deterioration trend of an individual bridge under any ratings.

Keywords: condition degradation; prediction model; semi-Markov process; technical state rating; concrete box girder bridge

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1. Introduction

Bridges play a key role in the arteries of the whole transportation network. However, many bridges experience degradation in load-bearing performance due to the aging of construction materials, the harsh environment and inappropriate management, which leads to a potential threat to the safety and reliability of the bridge system. With the increasing number of bridges and the demanding maintenance and management of highway network, research focus has changed from construction to management and maintenance. However, the maintenance strategies need to be decided according to the degree of bridge degradation. Therefore, due to the problems of structural aging, steel bar corrosion and other structural defects caused by long-term loading on bridges, it is crucial to construct an appropriate degradation model based on the regular inspection information of bridges [1].

There are many models available for bridge performance evaluation and prediction. Based on neural network and machine learning methods, Xia et al. [2] proposed an entire data-driven condition assessment framework for network-level bridges, including data integration, condition assessment and maintenance management. Lallam et al. [3] proposed a fuzzy hierarchical analysis (AHP) method to evaluate the damage state of bridges, which is used in the decision-making of the maintenance planning of masonry arch bridges, but the priority criteria are subjective. Martucci et al. [4] proposed the extreme value function theory (EFT), which provides a convenient tool for damage detection based on modal modes. Based on deep learning technology and a Bayesian network model, Lei et al. [5] proposed a multi-level time-varying defect analysis method and provided an overall evaluation framework for the bridge network according to inspection reports of bridges over many years. Liu et al. [6] provided a state assessment method based on variable weight synthesis method and grey relational degree theory to evaluate cable-stayed bridges. However, the research mainly focused on cable stress, and other components were not considered. In addition, it is necessary to study the impact of reinforcement and maintenance on the evaluation and prediction of concrete beam bridges. Allawi [7] verified through experimental testing and numerical analysis that the performance and method of using external prestressing to reinforce beams can effectively improve the bearing capacity of the reinforced beams. Allawi et al. [8] and Al-Sherrawi et al. [9] studied the mechanical performance of full-size post tensioned precast concrete beams with different node configurations. Vůjtěch et al. [10] applied Fe-Mn-Si shape memory alloy to reinforce a historic road bridge, which significantly improved the yield and fatigue capacity of the reinforced beam.

The stochastic model is also a commonly used method to predict the degradation process of the bridge structure. The stochastic model typically uses a state-based Markov chain model, which is constructed by using the transfer probability matrix obtained from the percentage prediction method [11]. The uncertainty and randomness of the degradation process of concrete bridges can be taken into account by the random model predictions [12–15]. The typical stochastic methods include Gamma process, Weibull process and Markov process, while the Markov model has been widely used in the degradation modeling of infrastructure in cases where concrete inspection data are available.

State-based stochastic Markov chain model is often applied in bridge management planning. By establishing a Markov chain model, the transfer probability of bridge components in different conditions can be modeled and analyzed, and the degradation of bridge components and their future damage development can be predicted. Yosri et al. [16] developed a stationary GA-based Markov chain model to effectively predict future bridge conditions based on historical data. Tao et al. [17] have proposed a novel hybrid Markov decision process model that integrates a discrete-time Markov decision process model for dealing with progressive deterioration and a continuous-time Markov decision process model for dealing with sudden earthquakes into a unified framework. Schöbi et al. [18] presented an enhanced variant of partially observable Markov decision processes (POMDPs) for the life cycle assessment and maintenance planning of infrastructure, which can achieve a better balance between accuracy and computational efficiency. Lethanh et al. [19] used Bayesian statistics and a Markov chain Monte Carlo simulation to propose a Poisson hidden Markov model for predicting the deterioration process of pavement structures.

In contrast to traditional Markov processes, semi-Markov can reflect real-time bridge state transitions, where the holding time of each state is assumed to follow a Weibull distribution. Wu et al. [20] proposed a life cycle optimization model based on the semi-Markov process, which makes the decision-making process of bridge management more quantitative and explicit. Thomas et al. [21] concluded that the semi-Markov model is more feasible and flexible than the traditional Markov chain model in predicting the deterioration of existing transportation infrastructure. Fang et al. [22] proposed a semi-Markov process model based on Weibull distribution for the prediction of urban bridge deterioration by considering the time-dependent reliability in the bridge deterioration process, and showed that the prediction accuracy of the semi-Markov model at the network level was better than that of the regression analysis method. Masovic et al. [23] introduced the semi-Markov decision process and found that determining the optimal strategy in a finite time range has high mathematical complexity. Zambon et al. [24] proposed a state rating model based on a semi-Markov process, which can overcome the shortcomings of the original model that did not take into account the properties of actual physical phenomena leading to deterioration.

In summary, the existing evaluation criteria and analysis methods have certain subjectivity. The simulation of bridge degradation process ignores a large amount of measured data and pays less consideration to bridge components. In addition, the traditional Markov process cannot capture the real-time bridge condition state transition, while the state transition of the semi-Markov process has the Markov property, and the time-varying semi-Markov can transform the qualitative inspection data into quantitative technical condition rating and prediction as well. Therefore, it is of great significance to study the degradation prediction of concrete box girder bridges based on the semi-Markov process.

This paper uses the semi-Markov model of Weibull distribution to analyze the inspection data of concrete box girder bridges in the highway network, and simulates the degradation of the technical states of the overall structure and the superstructure of highway bridges. This method can make full use of the bridge inspection data and technical condition evaluation data. According to the data, the box girder bridge is classified according to the bridge span and degradation rates; then, the technical condition degradation simulations are carried out. Considering the transition probability and waiting time distribution of the bridge state, the real-time bridge state is obtained to better describe the performance degradation law of the actual bridge and provide a more accurate prediction model for bridge degradation simulations.

2. Discrete State Degradation Process Random Simulation

2.1. Time-Varying Markov Chain Method

Time-varying Markov chain is an extended form of the Markov chain. The evolution of a Markov chain can be seen as a series of transitions between certain states under certain conditions. This process requires the property of memorylessness, meaning that the probability of future states depends only on the current state and not on the past states. For the discrete parameter stochastic process (X_t) with a discrete state space, the properties of a Markov chain can be represented as follows:

$$\mathrm{P}(X_{t+1} = i_{t+1} | X_t = i_t, X_{t-1} = i_{t-1}, \ldots, X_1 = i_1, X_0 = i_0) = \mathrm{P}(X_{t+1} = i_{t+1} | X_t = i_t) \quad (1)$$

where i_t is the process state at time t; and P is the conditional probability of a future event.

When the system degradation of state i is modeled based on the Markov chains, the transition probability, denoted as p_{ij}, from state i to state j in the next stage can be represented as:

$$\Pr(X_{t+1} = j \big| X = i) = p_{ij} \quad (2)$$

The transition matrix **P** is represented as follows:

$$\mathbf{P} = \{p_{ij}\}_{M\times M}, \text{ where } p_{ij} \geq 0 \text{ and } \sum\nolimits_{j=1}^{M} p = 1 \; for \; i,j = 1,2,\ldots,M \quad (3)$$

The dimension M of the transition matrix **P** depends on the number of possible states in the system, and the sum of probability of each row in this matrix is unity. For a system in state i, after n transitions, the transition probability matrix $\mathbf{P}^{(\mathrm{n})}$ for the system to change from state i to state j is given by:

$$\mathbf{P}^{(\mathrm{n})} = \mathbf{P}\cdot\mathbf{P}\cdot\ldots\cdot\mathbf{P} = \mathbf{P}^{\mathrm{n}} \quad (4)$$

where $\mathbf{P}^{(\mathrm{n})}$ is the probability of the system transitioning from state i to state j within n transition periods. When the transfer period is one year, $\mathbf{P}^{(\mathrm{n})}$ represents the probability of the system moving from state i to j in year n. The Markov model can be expressed as:

$$\mathbf{a}(n) = \mathbf{P}^n \cdot \mathbf{A}(0) = \mathbf{P}^n \cdot \mathbf{a}(0) \tag{5}$$

where $\mathbf{a}(n)$ is the state probability vector at time n; $\mathbf{a}(0)$ is the initial state probability vector and $\mathbf{P}$ is the state transition probability matrix.

In this article, the time-varying Markov chain process is used to obtain the deterioration model. For the time-varying Markov chain, the state transitions not only depend on the current state, but also on the duration of time spent in each state. The characteristics of the semi-Markov chain are that it can more accurately describe the duration of state changes and the temporal characteristics of the transition process. By comparing with traditional Markov chains, modeling and analysis of the time-varying Markov chain are more complex, requiring consideration of the transition probability and waiting time distribution of states. The probabilities of bridge states can be influenced and altered by external factors, such as environmental conditions and vehicle loads. Therefore, the use of the semi-Markov chain is more appropriate for the bridge performance degradation model.

2.2. Performance Degradation Modelling

In the process of assessing bridge degradation, the structure cannot transition directly from one state to another state within a short period of time. Additionally, the structure cannot transition from a worse state to a better state without any maintenance. Therefore, the transition matrix can be represented as:

$$\mathbf{P} = \begin{bmatrix} p_{11} & p_{12} & 0 & 0 & 0 \\ 0 & p_{22} & p_{23} & 0 & 0 \\ 0 & 0 & p_{33} & p_{34} & 0 \\ 0 & 0 & 0 & p_{44} & p_{45} \\ 0 & 0 & 0 & 0 & p_{55} \end{bmatrix} \tag{6}$$

In a traditional Markov chain, the transition probability matrix $\mathbf{P}$ is determined by minimizing the difference between the inspected state values and the predicted states obtained from bridge inspections:

$$\min_{p_{ij}} \sum_{k=1}^{K} \left\| \mathrm{B}_k - \mathbf{a}(0)^{\mathrm{T}} \mathbf{P}_{\mathrm{n}_k} \mathbf{s}^{\mathrm{T}} \right\| \tag{7}$$

where B_k is the inspection value of the bridge condition at the degradation cycle; k is the total number of inspection values; $\mathbf{s}^{\mathrm{T}}$ is the transpose of the bridge state space $\mathbf{s} = [1,2,3,4,5]$, corresponding to bridge ratings from grade one to grade five (CR1–CR5); $\mathbf{a}^{(0)} = [1,0,0,0,0]^T$ is the initial state probability. The grade ranges and qualitative descriptions corresponding to the condition ratings from grade one to grade five (CR1–CR5) are provided in [21], as shown in Table 1.

Table 1. The state classification of Chinese highway bridges [25].

Condition Rating	Grade Range	Damage Description
1	[95, 100]	New condition, fully functional.
2	[80, 95)	Small defects, no impact on the functionality of the bridge.
3	[60, 80)	Moderate defects, still able to maintain normal functional use.
4	[40, 60)	Major components have significant defects, affecting the functionality of the bridge or reducing its load-bearing capacity, making normal use uncertain.
5	[0, 40)	Major components have severe defects, rendering the bridge unusable and posing a risk to bridge safety. The bridge is in a dangerous state.

In the semi-Markov process, the state space remains in a particular state for a given time and then transitions to another state. The waiting time at any state can be modeled as a random variable with a Weibull distribution. The probability density function $f_i(t)$ and survival function $S_i(t)$ of state i as a function of time t are represented as:

$$f_i(t) = \lambda_i \kappa_i (\lambda_i t)^{\kappa_i - 1} \exp[-(\lambda_i t)^{\kappa_i}] \tag{8}$$

$$S_i(t) = \exp[-(\lambda_i t)^{\kappa_i}] \tag{9}$$

where λ_i and κ_i are the scale and shape parameters of the Weibull distribution in state i, respectively.

From Equation (7), to obtain the semi-Markov transition matrix of the bridge, it is necessary to calculate the probability $p_{i,i+1}$ of transitioning from state i to the next state. Therefore, considering the waiting time $[T_1, T_2, T_3, T_4]$ corresponding to state $i = [1, 2, 3, 4]$ as a random variable, if the deterioration process is in state i at time t the conditional probability of the bridge transitioning to the next state $i + 1$ in the next time step Δt (typically one year) is expressed as [26]:

$$p_{i,i+1}(t) = \frac{f_{1\to i}(t)\Delta t}{S_{1\to i}(t) - S_{1\to(i-1)}(t)} \tag{10}$$

where $f_{1\to i}$ is the probability distribution function (PDF) of waiting time $T_{1\to i}$; $T_{1\to i}$ is the cumulative waiting time from state 1 to state i; $S_{1\to i}$ and $S_{1\to i-1}$ are the survival functions of waiting time $T_{1\to i}$ and $T_{1\to i-1}$, respectively.

The current objective is to estimate the scale parameter λ_i and the shape parameter κ_i for the inspection data. There are several methods to estimate the parameters, such as expert opinion method and maximum likelihood estimation. In this paper, based on the degradation curves, it is assumed that the survival probability $S_i(\tau_i)$ corresponding to the average waiting time of each state is 50%, and the estimation of the Weibull distribution's scale parameter λ_i and shape parameter κ_i is given by [27]:

$$\begin{array}{l} \text{Min} \sum_1^{\tau_i} | \exp[-(\lambda_i t)^{\kappa_i}] - \overline{p}_i^{\frac{t}{\tau_i}} |^2 \\ \text{Subject to} : \exp[-(\lambda_i \tau_i)^{\kappa_i}] = \overline{p}_i \end{array} \tag{11}$$

where $\overline{p}_i$ is the survival probability at time $T_i = \tau_i$, obtained from assumptions. Based on the determined Weibull distribution parameters of the rating waiting time $[T_1, T_2, T_3, T_4]$, the cumulative waiting time distributions for State 1+2, State 1+2+3, and State 1+2+3+4 can be calculated using Monte Carlo simulations.

After obtaining the Weibull distribution parameters λ_i and κ_i for any state i, the probability transition matrix for the improved semi-Markov process for state i can be determined using Equation (11). The probability distribution of the state in year n can be obtained from the probability transition matrix and the state probability distribution, determined by:

$$\mathbf{a}(t) = \mathbf{a}(t-1)\mathbf{P}^{t-1,t}(t) \tag{12}$$

where $\mathbf{P}(t)$ is the probability transition matrix at time t years; $\mathbf{a}(t-1)$ is the state probability distribution in year $t - 1$.

By multiplying the state probability distribution at time t by the transposition of the bridge state space $\mathbf{s} = [1, 2, 3, 4, 5]$ the expected value of the state rating at time t is obtained from the following:

$$\mathrm{e}(t) = \mathbf{a}(t-1)\mathbf{P}^{t-1,t}\mathbf{s}^T \tag{13}$$

The flow chart for determining the probability distribution of bridge ratings using the proposed method is shown in Figure 1.

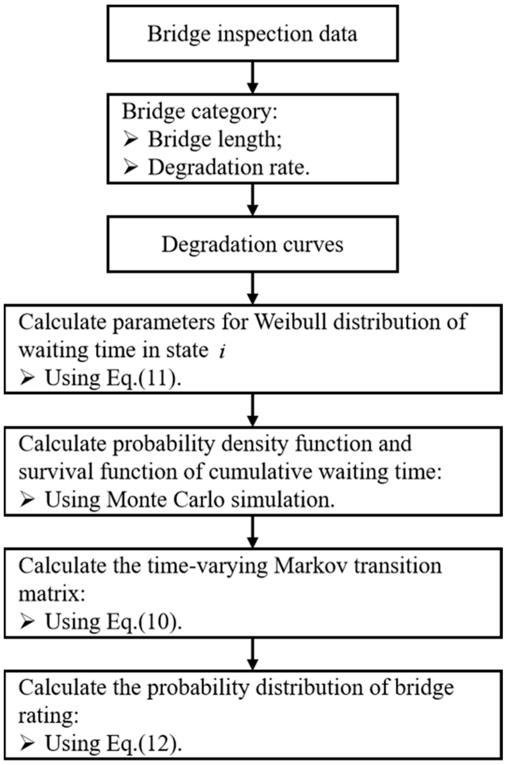


Figure 1. Calculation flow chart of probability distribution of bridge rating.

3. Deterioration Modelling of Highway Bridges

3.1. Bridge Technical Condition Evaluation

The assessment of the current condition of existing bridges of a highway network forms the basis for bridge degradation prediction and maintenance decision-making. In China, the technical condition assessment of highway bridges is mainly undertaken in accordance with [25]. Periodic inspections are carried out to assign bridge technical condition scores and determine the technical condition rating.

During inspections, bridges in the highway network are divided into three components for inspection, i.e., bridge deck system, superstructure and substructure. Bridge inspectors visually assess the extent of deterioration for each component and then assign the corresponding values. Based on the standardized criteria, the technical condition scores for each component are calculated; then, the technical condition scores of each bridge components, and the bridge as a whole are obtained. Finally, as shown in Table 1, the technical condition rating of the bridge is determined.

3.2. Deterioration Curve

The inspection data for approximately 30 years for a total of 1773 concrete box girder bridges in Jiangxi province in China are collected. Among these bridges, a total of 1173 are the prefabricated concrete box girder bridges, accounting for approximately 65% of the total number of bridges. Therefore, this study primarily focuses on the degradation prediction of prefabricated box girder bridges. The construction date of the concrete box girder bridges is illustrated in Figure 2.

To construct a scientifically sound degradation model for bridge technical conditions at the highway network level, a substantial amount of inspection data are required. In practice, insufficient data, caused by the limited number of bridges, make it difficult to determine the waiting time for each condition; thus, the reasonable Weibull distribution-based semi-Markov degradation model for bridges may not be easy to obtain. The differences in degradation patterns of bridges for the same bridge type exist in services, but could be neglected in the current condition assessments. This study takes advantage of the large quantity of data available for prefabricated box girder bridges and divides the bridge into multiple types for in-depth analysis.

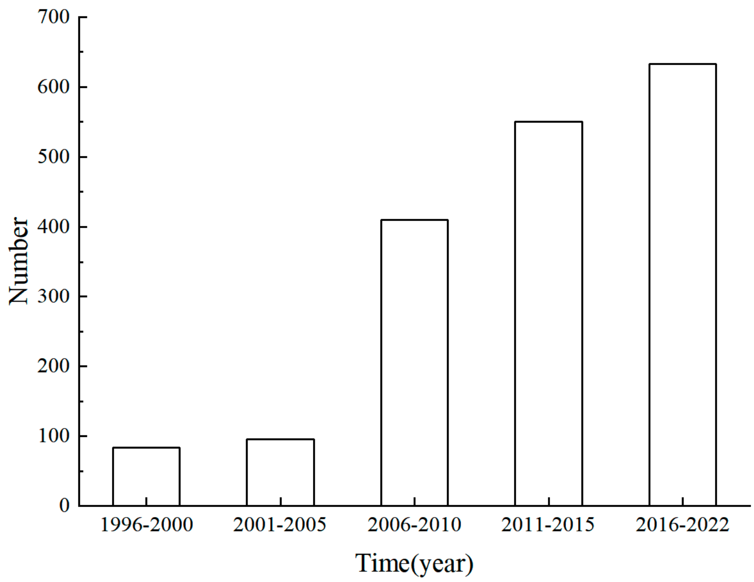


Figure 2. Number of concrete box girder bridges built in different years.

Through the collection and organization of the detection data, we found that there are differences in the degree of degradation of different bridge sections, and there are also differences in the degradation rate of the same bridge length. At present, there are also relevant studies in the literature indicating a correlation between bridge length and the degradation rate of technical conditions [28]. Therefore, in this study, the prefabricated box girder bridges are classified into nine categories based on bridge length and degradation rate. Firstly, bridges are categorized into three groups based on bridge length, i.e., 0–100 m, 100–200 m and >200 m. Secondly, each type of bridge length is divided into three types based on degradation rate, i.e., fast, medium and slow degradation. The degradation rate (fast, medium and slow degradation) of the bridge is determined as the maximum value between the ratio of the detection score to the bridge age and the ratio of the difference from two detection scores to the detection interval. Divide the degradation rate interval to obtain bridges with fast, medium and slow degradation. According to the above classification method, the overall bridge and the superstructure are divided into nine categories. The linear regression method is employed to fit the degradation curves over time for each category of prefabricated box girder bridges, for both the overall condition and the superstructure condition, as shown in Figures 3 and 4. It is worth noting that the service time of the bridge in this paper is relatively short, making it difficult to obtain a complete degradation curve. However, we have added data on the degradation of the bridge to ratings 4 and 5 after consulting the relevant literature, allowing the model to predict the performance of bridges with longer service periods. Figure 3 shows the results for the degradation curves of the whole bridge system with various bridge lengths; the degradation curves are obtained from the relevant inspection data for the group of bridges by the curve fitting method.

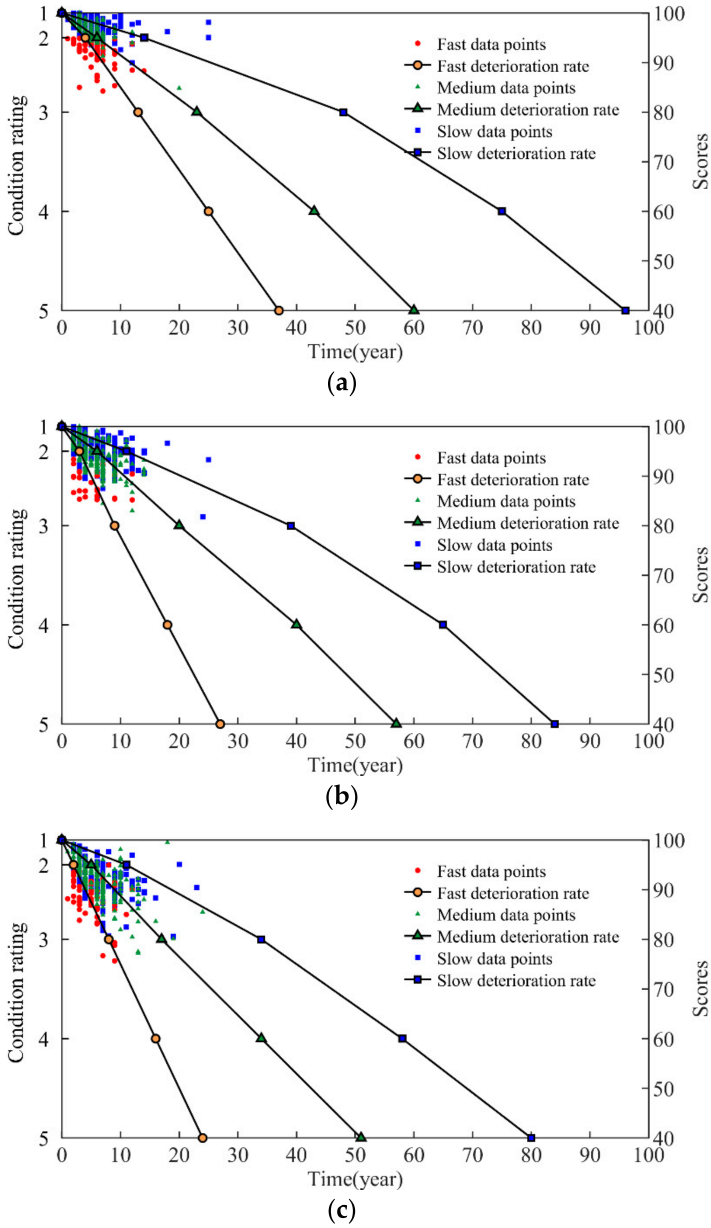


Figure 3. Degradation curves for bridges' overall technical condition: (**a**) whole bridge with length 0~100 m; (**b**) whole bridge with length 100~200 m; (**c**) whole bridge with length > 200 m.

From the results, in the case with moderate degradation rates, the overall technical condition of the bridge with lengths of 0~100 m, 100~200 m and >200 m from condition state 1 to state 3 takes 23 years, 20 years and 17 years to degrade, respectively. This indicates that as the bridge length increases, the degradation rate of the bridge technical condition also increases.

Figure 4 shows the degradation law of the superstructure technical conditions for various bridge lengths. Here, in the case with a moderate degradation rate and a bridge length of 0–100 m, it takes approximately 23 years for the overall condition to degrade from a good condition to rating 3, while for the superstructure with a bridge length of >200 m, it takes around 16 years, indicating that the deterioration rate of the service performance of the superstructure degrades faster mainly due to the significant impact of traffic loads.

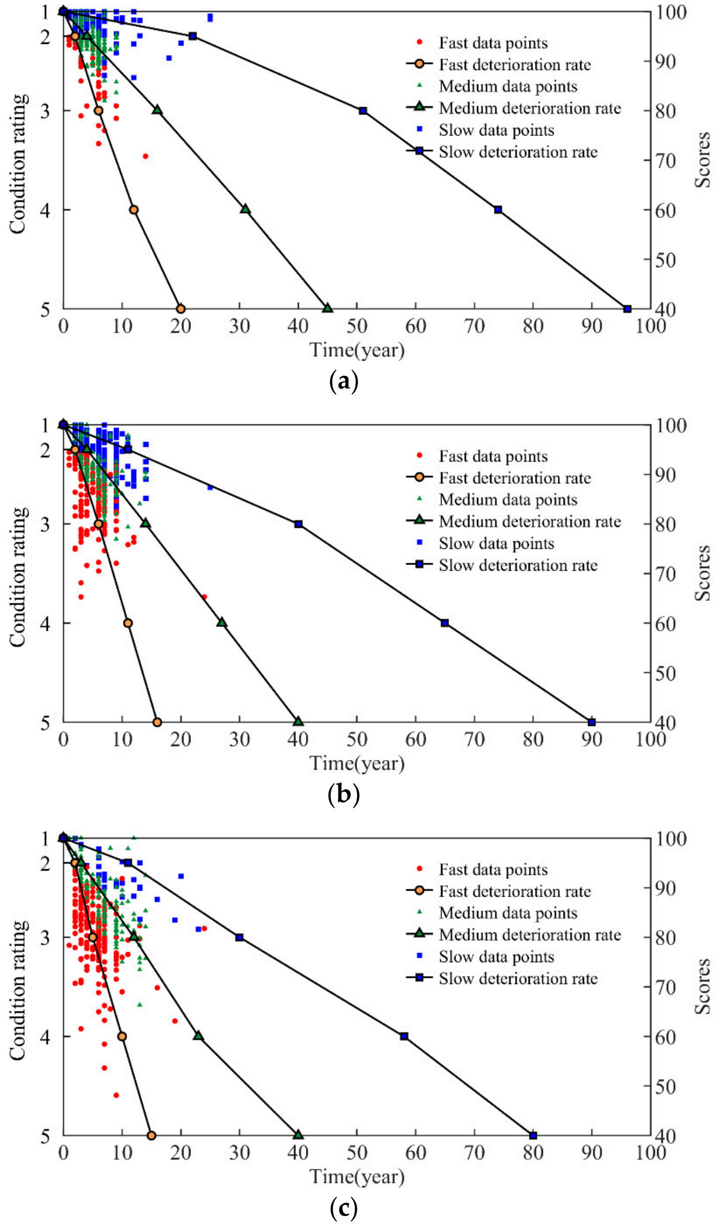


Figure 4. Degradation curves of superstructure technical condition: (**a**) superstructure with length 0~100 m; (**b**) superstructure with length 100~200 m; (**c**) superstructure with length > 200 m.

4. Reliability Assessment and Prediction

4.1. Bridge Network

As mentioned earlier, there is a certain correlation between the overall and superstructure degradation and the bridge length. Generally, as the bridge length increases, the degradation of the technical conditions of the bridges accelerates. Furthermore, the analysis of historical inspection data indicates that a significant number of bridges deteriorate at a moderate degradation rate. Therefore, this study primarily focuses on the analysis of the overall and superstructure degradation of prefabricated box girder bridges with a length greater than 200 m at the medium degradation rate.

During the calculation for the transition matrix using the time-varying Markov chain method, if there are waiting time data for different condition ratings of the bridge, the Weibull distribution parameters can be estimated with the curve fitting method. However, due to limited data availability, the average waiting times for each condition rating to estimate the Weibull distribution parameters for the overall and superstructure condition ratings are obtained using Equation (11). The estimated parameters are presented in Table 2.

Table 2. Parameter estimation of Weibull distribution with different ratings.

Grade	Whole Bridge		Superstructure	
	Scale Parameter	Shape Parameter	Scale Parameter	Shape Parameter
1	0.1750	2.7433	0.2729	1.8329
2	0.0730	2.7794	0.0980	2.9121
3	0.0532	3.6581	0.0789	2.5968
4	0.0532	3.6581	0.0532	3.6581

According to the Weibull distribution parameters in Table 2, the Monte Carlo numerical simulation is conducted to obtain the probability density functions and survival functions for the cumulative waiting times of different condition ratings of the bridges in the highway network. These functions are shown in Figures 5 and 6. From Figures 5 and 6, it can be observed that the service time corresponding to the peak value of the probability density function of cumulative waiting time in Figure 5 is the same as that corresponding to a 50% survival probability in Figure 6 for both the overall condition and the superstructure condition, indicating the correctness of the model proposed in this study.

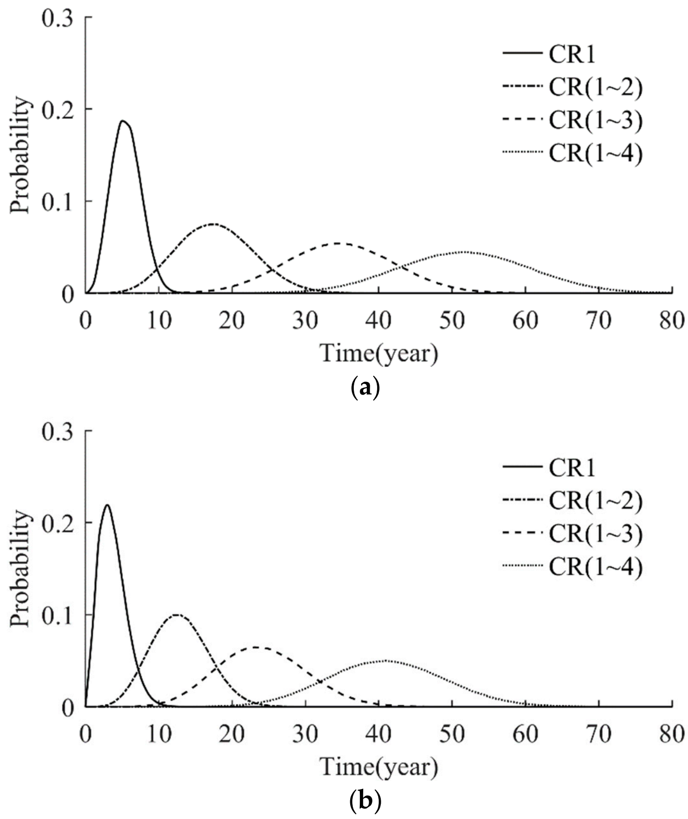


Figure 5. Probability density function of cumulative waiting time for different ratings: (**a**) bridge overall; (**b**) superstructure.

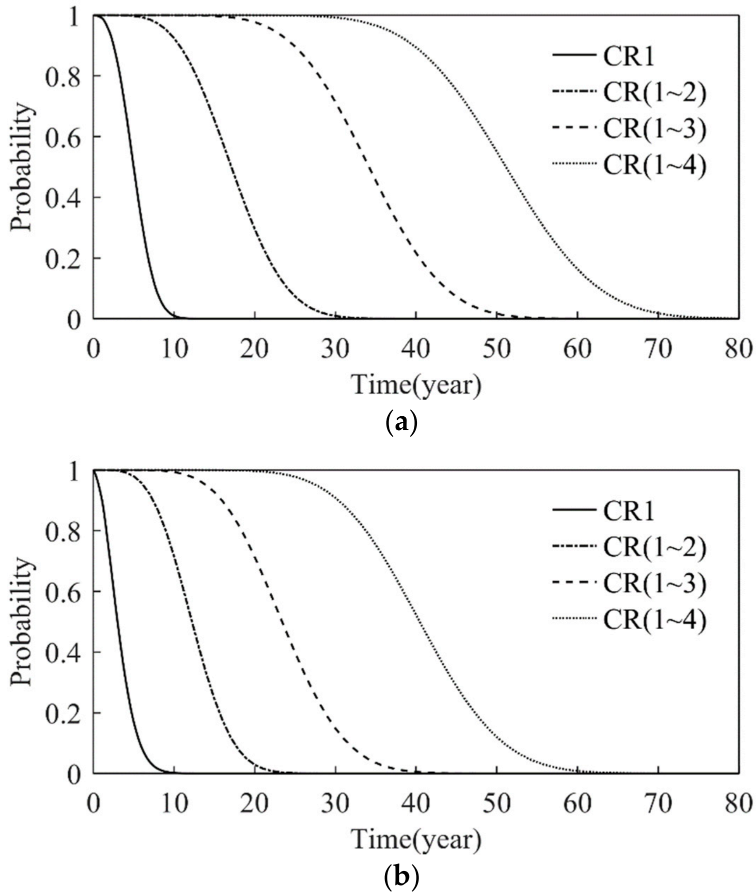
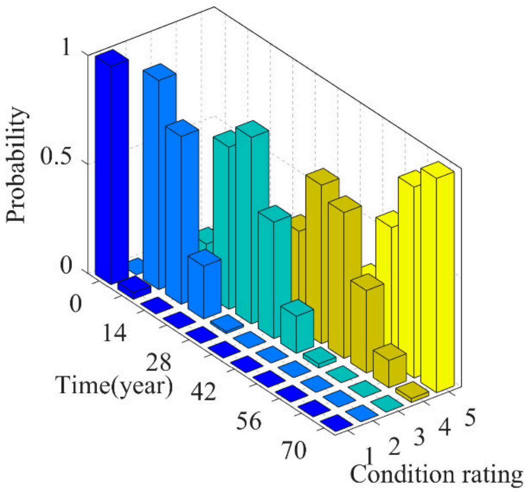


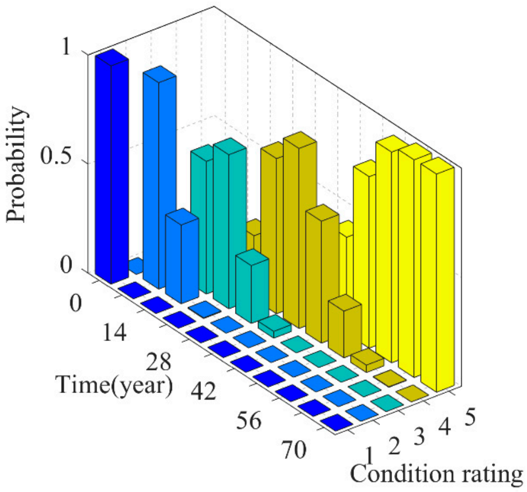
Figure 6. Cumulative waiting time survival function for different ratings: (**a**) bridge overall; (**b**) superstructure.

In Figure 6, CR (1–4) represent the survival functions for the cumulative waiting times of condition ratings 1 to 4. The expected lifespans for the overall condition and the superstructure condition at a 50% survival probability are approximately 52 years and 41 years, respectively. These values agree closely with the lifespans shown in the degradation curves, which demonstrates that the proposed degradation model can effectively predict the degradation trends of bridge technical conditions at the highway network level.

After the probability density functions and survival functions for the cumulative waiting times of different condition ratings are obtained, the transition probability matrix for each time interval (t = 1) can be calculated from Equation (10). The transition probability matrix is then applied to Equation (12) to obtain the probability distribution for different condition ratings. Figure 7 illustrates the evolution of the distribution of all condition states for the overall condition and the superstructure condition of the bridges in the highway network. It is assumed that the probability distribution for rating 1 is unity at time t = 0, and there are no maintenance or repair actions. For the overall condition, 44% of the bridges do not degrade to rating 5 after 52 years in service, and for the superstructure condition, almost all bridges have degraded to rating 5 after 60 years in service.



(**a**)



(**b**)

Figure 7. Probability distribution of different condition ratings of overall bridge and superstructure over time: (**a**) bridge overall; (**b**) superstructure.

4.2. Individual Bridge Case Study

The method for evaluating the degradation of technical conditions for an individual bridge is similar to that used for assessing the degradation of bridges in a highway network, shown in Figure 8. Here, the technical condition degradation is predicted for three components, i.e., bridge bearing, superstructure and bridge overall. In this paper, a prefabricated concrete box girder bridge with a length of 217 m built in 2012 is adopted for the individual bridge case study; the bridge was inspected in 2015, 2018 and 2021, and the field inspection results are summarized in Table 3.


Figure 8. A prefabricated concrete box girder bridge for case study.

Table 3. Technical state scores for the bridge.

Inspection Time	Bearing	Superstructure	Bridge Overall
Year 2015	100	92.8	96.08
Year 2018	81.43	88.32	94.24
Year 2021	75.33	82.23	92.17

By the linear regression fitting of technical state scores, the waiting times of rating 1 and rating 2 are 3 years and 7 years for the superstructure and 6 years and 16 years for the bridge overall, respectively. By comparing the degradation curves in Figures 3c and 4c, the technical state scores of the superstructure and the bridge overall can be classified as the moderate deterioration rate. The bearing has been degraded to rating 3 at present, and the waiting times of bearing ratings 1 and 2 are about 4 and 3 years, respectively. Due to the limited amount of inspection data, the waiting time of rating 3 and rating 4 are difficult to obtain. The missing data are supplemented from the literature as indicated in Figures 2 and 3, and their complete degradation curves are provided, as shown in Figure 9.

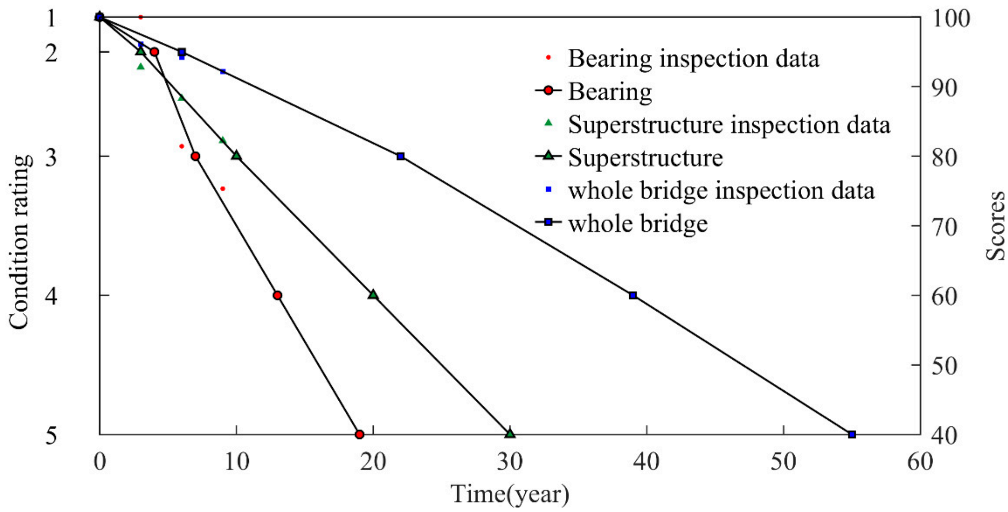
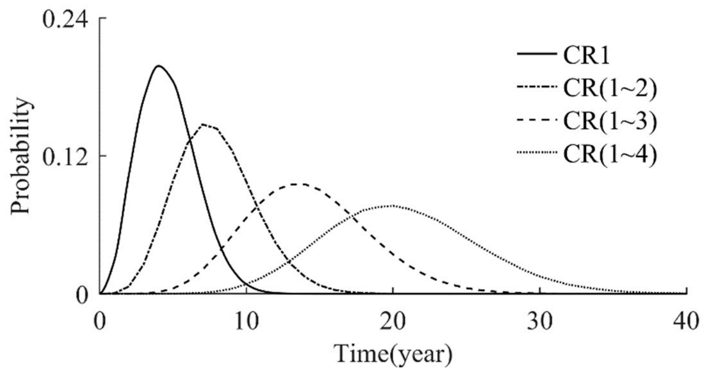


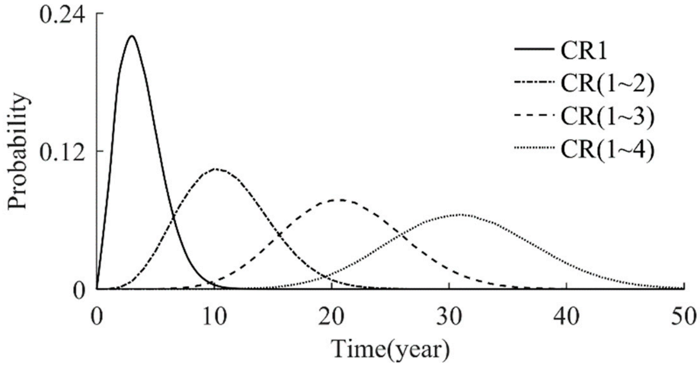
Figure 9. Technical condition rating degradation curves.

Figures 10 and 11 show the results for estimating the cumulative wait time for ratings by using Monte Carlo. As expected, the time for the maximum probability density for three bridge components is approximately the same as that corresponding to a 50% survival probability.

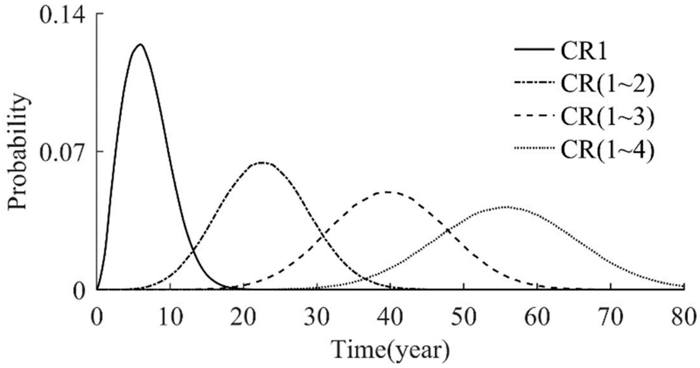


(**a**)

Figure 10. *Cont.*



(**b**)

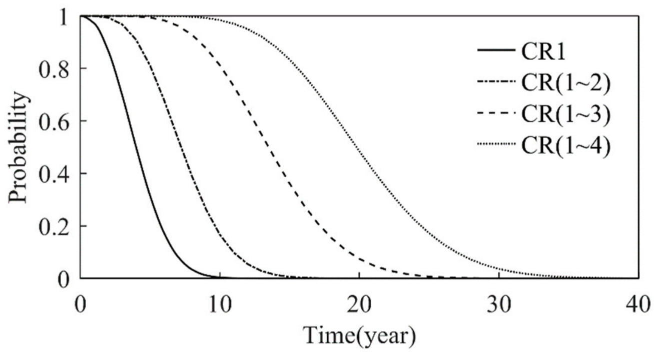


(**c**)

Figure 10. Probability density function of cumulative waiting time for different bridge components: (**a**) bearing; (**b**) superstructure; (**c**) whole Bridge.

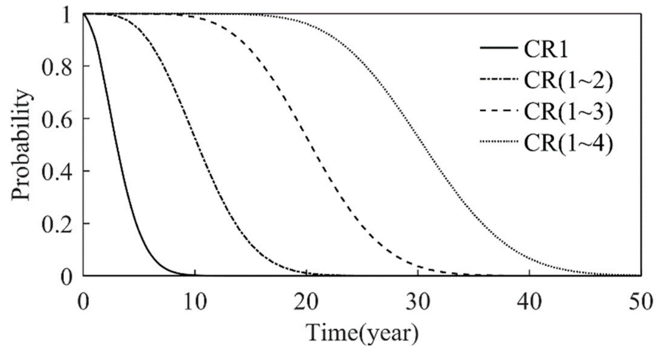
In Figure 11, the life expectancy of the bridge bearing, superstructure and the bridge overall with CR (1~4) at 50% survival probability is given as 20 years, 31 years and 55 years, respectively, which is basically consistent with the time shown by the degradation curves.

Figure 12 shows the semi-Markov transfer various probabilities of the bearing, superstructure and the bridge overall, where p_{ij} represents the probability of transferring the ith condition rating to the jth condition rating. It can be seen that under the same bridge age, the probability p_{45} of the bearing transferring from CR4 to CR5 is greater than that of the superstructure and the bridge overall. Compared with the bearing and the bridge overall, the increase in superstructure p_{12} is the most obvious, since the degradation of the superstructure from CR1 to CR2 is the fastest for the inspection data.

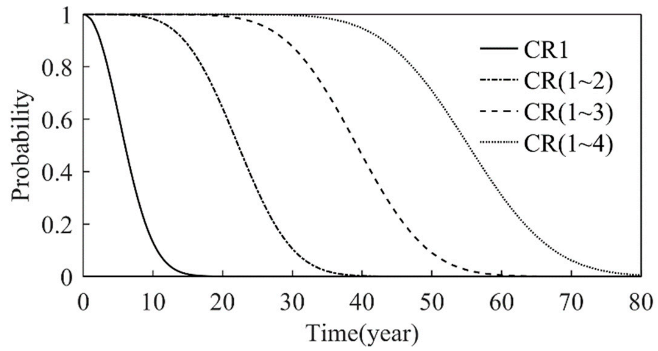


(**a**)

Figure 11. *Cont.*



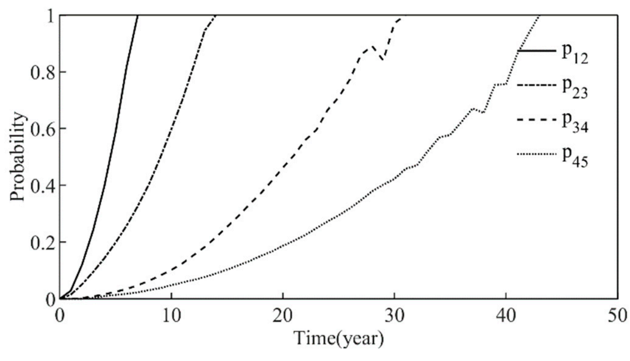
(**b**)



(**c**)

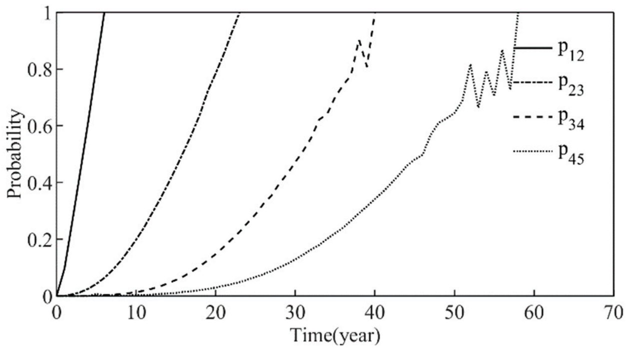
Figure 11. Cumulative waiting time survival function for different bridge components: (**a**) bearing; (**b**) superstructure; (**c**) whole bridge.

Similarly, the semi-Markov model based on the Weibull distribution is utilized to predict the change in the technical state rating probability of the bridge over time, as shown in Figure 13. As can be seen from Figure 13, compared with the bearing and superstructure, the technical condition of the bridge overall deteriorates the slowest, and the probability of CR5 disappears after about 80 years in service. For the bearing in Figure 13a at year 15, the probabilities of CR3, CR4 and CR5 are approximately 40%, 49% and 11%, respectively. In the following 10 years, the probability of CR4 first increases and then decreases, while the probability of CR3 continues to decrease, indicating that the bearing could be within CR4 or even close. It can be seen from Figure 13c that the time corresponding to the 50% probability from CR1 to CR5 is approximately 6 years, 23 years, 40 years and 57 years, respectively, which is only 1 or 2 years different from the times shown by its degradation curve, indicating that the model can better predict the degradation trend of the technical condition of individual bridges.

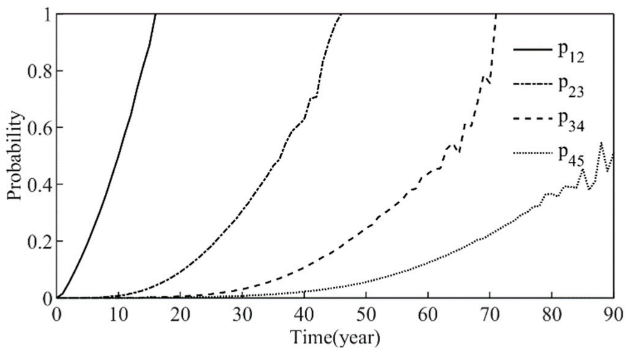


(**a**)

Figure 12. *Cont*.

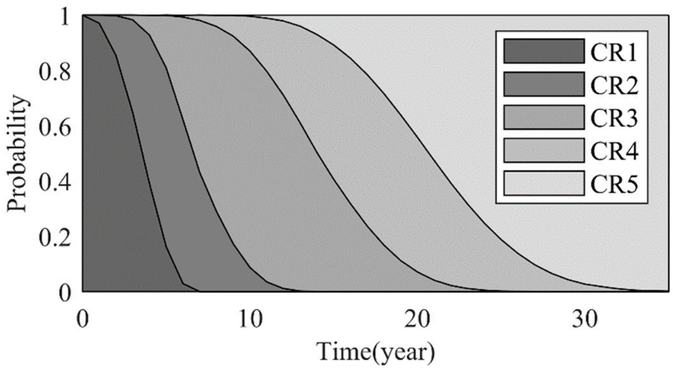


(**b**)

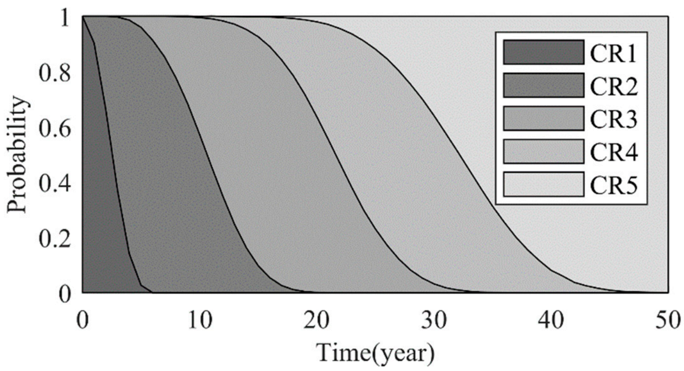


(**c**)

Figure 12. Semi-Markov transition probability with time for different components: (**a**) bearing; (**b**) superstructure; (**c**) whole bridge.

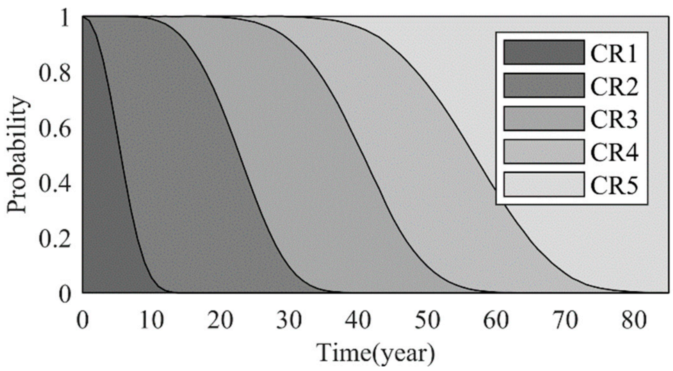


(**a**)



(**b**)

Figure 13. *Cont*.



(**c**)

Figure 13. Probability distribution of technical state ratings over time for different bridge components: (**a**) bearing; (**b**) superstructure; (**c**) whole bridge.

5. Conclusions

This study utilizes the regular inspection data of the prefabricated prestressed concrete box girder bridges located on the highway network, and proposes a time-varying deterioration model for the technical conditions of the structural components of both the group and individual bridges. The following main conclusions can be drawn:

(1) The degradation curves of the technical condition of the superstructure and bridge overall can be obtained from the inspection data, classified as fast, medium and slow degradation curves and with three deterioration rates, i.e., fast, moderate and slow. It is found that when the bridge length increases, the degradation rate of the technical condition also increases.

(2) Over the next 30 years, the proportion of the bridges in technical condition ratings 1 and 2 gradually decreases in the highway network, while the number of bridges in technical condition ratings 3 and 4 increases rapidly. The superstructure of the bridges, as the main load-bearing component, is more significantly influenced by traffic loads, resulting in a higher degradation rate compared to the bridge overall. When t = 21, the proportion of CR = 3 and CR = 4 in the highway network was about 0.73 and 0.02, respectively, and after 7 years, the proportion of CR = 3 and CR = 4 was about 0.85 and 0.13, respectively.

(3) The time-varying Markov model, based on the Weibull distribution using the existing inspection data, can effectively predict the degradation of technical conditions for both groups of bridges in the highway network and individual bridges. This method is helpful for bridge managers to accurately grasp the degradation law of bridge performance and make reasonable economic resource allocation and optimal maintenance timing decisions. In the future, the established time-varying Markov model will be modified by using the newly added detection data of bridges with the multiple service environments and longer service life, so as to establish a more general and practical bridge degradation model.

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Conflicts of Interest: Author Zewen Zhu, Kuai Ye, Xinhua Yu, Zefang Lin, Gangzong Xu and Shoushan Lu were employed by the company. The remaining authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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