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Machine Learning based Health Status Assessment of Super-span Suspension Bridges

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Abstract: With the rapid development of bridge design and analysis theory, building materials development and construction technology, more and more long-span bridges are built across rivers and seas. At the same time, the bridge construction scheme of over 1000 meters of bridges across rivers and seas is becoming more and more mature. Among them, the mainstream long-span bridges are suspension bridge (SB). The accuracy of research on key structure technology of bridge body needs to be continuously improved to ensure the structural safety of long-span bridges. Therefore, based on machine learning (ML) technology, the health status of super long span SBs is evaluated in this paper. The purpose and significance of long-span bridge structure health monitoring are briefly analyzed. Through the analysis of ML neural network algorithm, the evaluation model index layer is determined; finally, this paper takes the supporting project as an example to evaluate the safety status of the completed SB, which verifies the feasibility and effectiveness of the algorithm in this paper.

1. Introduction

The development of bridge health detection is becoming more and more mature, and it is widely used in the health monitoring of various bridges during the operation period. This is due to the real-time, visibility, long-term and stability of the health monitoring system. In recent years, many methods have emerged in the field of bridge health monitoring and safety assessment, among which the analytic hierarchy process (AHP) combined with expert evaluation system is widely used. However, this method does not give enough consideration to the relative relationship between various evaluation parameters in the evaluation, and the overall rating of the main construction of the whole structure is not comprehensive and to the point. Therefore, this paper uses the neural network of ML technology to evaluate the bridge safety,

For long-span bridges, relevant bridge health monitoring systems need to be set up after completion to timely and comprehensively monitor the overall conditions during bridge operation.

Many long-span bridges at home and abroad are equipped with bridge structure monitoring systems. Such health monitoring systems monitor not only the structural status of the bridge itself, but also the bridge operating environment. These health monitoring data are real-time and scientific. However, the current health monitoring system focuses more on the real-time of bridge health monitoring data [1]. Although the methods of bridge damage location and evaluation are constantly discussed in China, the research in this field is extremely difficult due to the complex structure of long-span bridges and the large workload, which also leads to the dilemma that a large number of bridge health monitoring data cannot be used reasonably. Therefore, it is necessary to explore a safety assessment method based on ML, which can evaluate and timely feedback the bridge operation status and safety status [2].

In recent years, relevant researchers at home and abroad have put forward relevant evaluation algorithms such as fuzzy mathematical model and neural network model. Based on ML technology, this paper evaluates the health status of super span SBs. The bridge monitoring index is selected as the bottom neuron, and BP neural network is established. When selecting the neural network, the algorithm is optimized, and the algorithm that is more in line with the safety assessment requirements of long-span SBs is selected by comparison. It is proposed to introduce the fuzzy neural network structure as the main frame, combine the learning algorithm of BP neural network, collect the bridge monitoring data for sample data processing, and bring it into the model training, Finally, a network meeting the requirements of engineering accuracy is formed through training, and a reasonable bridge health assessment network is established [3-4].

2. Health Assessment and Analysis of Super Span SBs

2.1. Purpose and Significance of Long-Span Bridge Structure Health Monitoring

With the rapid development of bridge engineering technology, there are more and more cable-stayed bridges and SBs. Although reasonable structure design and construction control can ensure the safe use of bridge structures, there are still some problems in understanding complex structures, and many invisible factors cause major hidden dangers to the safe operation of bridge structures. In order to ensure the safe and normal operation of large bridges, it is very important to know the safety status of bridges in real time through health monitoring. Through health monitoring of long-span bridges, not only the safety status of the structure can be known in real time, but also the structural design scheme can be improved [5].

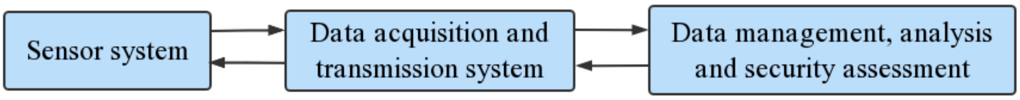

Figure 1. Subsystem composition of long-span bridge health monitoring system

2.2. Design Principles of Long-Span Bridge Structure Health Monitoring System

The principle of primary and secondary purpose and function. In the design of long-span bridge structural health monitoring system, the purpose and function of the system should be taken as the most important principle. The main purpose of the system is to understand the working conditions of the bridge in real time, and other purposes are taken as auxiliary.

Principle of function and cost optimization. Generally speaking, the cost of installing a health monitoring system is relatively high. Therefore, it is necessary to optimize the functions and costs of the health monitoring system [6-7].

System reliability principle. The reliability of health monitoring system is one of the important design principles of long-span bridge structure health monitoring system, which mainly depends on the reliability of each subsystem.

The principle of combining real-time and regular monitoring. In the design process of the health monitoring system, the combination of real-time monitoring and regular monitoring should be adopted according to the different monitoring contents of the health monitoring system.

The sensor system is the basis for the bridge structure health monitoring system to realize all its monitoring items and functions. Its main task is to sense the structural response signal of the bridge structure operation state through various types of sensors, and transmit the sensor signal to the control center of the health monitoring system as the important data for the bridge structure safety evaluation [8-9].

2.3. Health Status Assessment of Super Span SBs

The variation of SB construction quality will inevitably affect the final bridge completion state of the SB, and the bridge completion state has a great impact on the later operation stage of the bridge, so it is necessary to evaluate the safety state of the SB [10].

At present, the evaluation of the bridge completion status is mainly based on the quality acceptance of the completed construction, which is mainly evaluated from two aspects. One is to check the technical data of the construction process and score different components of the bridge, so as to obtain the overall score of the overall structure, so as to grade the bridge construction quality; the other is to evaluate the bridge status through inspection. At present, the main inspection items include appearance inspection and static and dynamic load test [11]. The first kind of evaluation has the advantage that it generally needs to track the whole construction process, and can reflect the quality problems in the bridge construction process to the evaluation of the completed bridge state. However, its disadvantage is that the evaluation requires more data and it is difficult to classify statistics. The second evaluation method has the advantages of short evaluation cycle and few indicators; however, its disadvantage is that it is relatively intuitive. Static and dynamic load tests can only evaluate the safety status of the bridge at the later stage of the bridge, but it is difficult to find hidden quality problems during the construction process [12-13]. Therefore, it is necessary to propose a method that can not only reflect the construction quality, but also avoid large amount of data and reduce the evaluation difficulty and workload. Based on the variability of construction quality, the safety status of the completed SB should be quickly and effectively evaluated.

In this paper, the main ML algorithm is introduced into the evaluation of the safety state of the completed SB, and the evaluation index is proposed according to the location and impact of the construction quality variation. Then, the principal component is calculated, and the safety state of the completed SB is evaluated according to the comprehensive score of the principal component.

It is necessary to select a comprehensive and reasonable evaluation index [14] to evaluate the completed safety status of SBs. Due to the wide variety and quantity of SB components, different material properties, complex construction procedures and huge data of construction quality control, if all of them are selected into the evaluation index system, the evaluation workload will be increased and the impact of main quality variation cannot be reflected, so the evaluation results are not accurate enough. Therefore, when selecting the evaluation indicators, it is necessary to select the factors with great influence on construction quality variation as the evaluation indicators [15-16].

According to the construction quality control points of each component of the SB and the parts prone to construction quality variation during the construction process, 8 types of construction quality variation can be obtained, mainly including anchor settlement deviation, anchor rod deflection angle, main tower longitudinal deviation, main cable damage, main cable erection (main cable rise span ratio), cable clamp deviation, steel box girder weight deviation, steel box girder welding residual stress [17]. The influence of the construction quality deviation of each component of the SB on the finished bridge state is reflected in the influence on the stress state of the anchorage, main tower, main cable, suspender, anchor tie rod, and steel box girder. Based on this, five indicators, namely, the tensile safety of the main tower concrete, the safety of the main cable, the safety of the suspender, the safety of the tie rod, and the stress safety of the steel box girder, are extracted [18].

The above safety indicators represent the safety of each important component and seem independent, but from the perspective of the variability of the construction quality of the affected indicators, there is a certain correlation between the indicators.

According to the rule of permissible effects:

$$S \leq [S] \tag{1}$$

The security degree of the structure can be defined as:

$$K_s = \frac{[s]}{s} \tag{2}$$

Where s is the most unfavorable effect under various load combinations, [s] is the design strength, and the structure is in a safe state when s ⩽ [s]; S is the structural safety degree, representing the safety reserve capacity of structural resistance. The greater the structural safety degree s, the higher the structural safety reserve. The evaluation index system is shown in Figure 2.

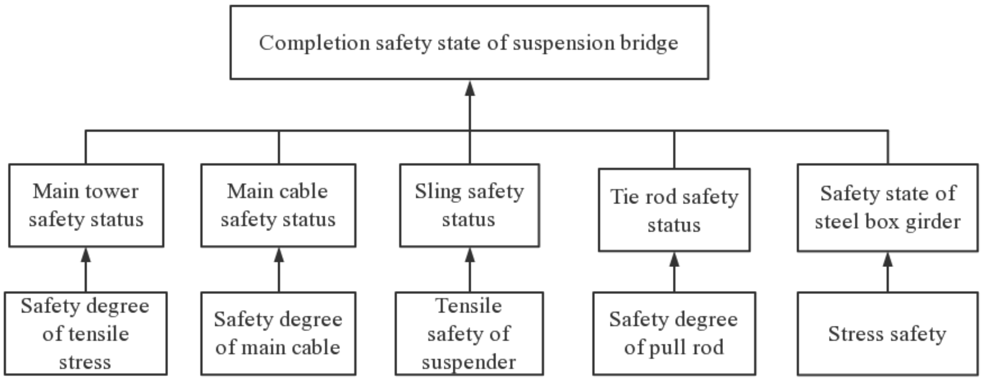

Figure 2. Evaluation index system of initial safety state of SB

3. Analysis of ML Algorithms

3.1. ML

Considering the complexity of each main component of SB and the adaptability of the algorithm, the algorithm of BP neural network is combined in the determination of the algorithm. BP algorithm is widely used in neural network, usually in feedforward network model. Using the above learning methods for training and learning, the algorithm can converge quickly, so as to achieve the required relationship between input and output. In addition, the BP algorithm of improved gradient descent momentum is used in each training of the network, and the network error function Ep is:

$$E=\sum_{i=1}^{T}E_p, E_p=\frac{1}{2}\sum_{k=1}^{M}(Y_k-y_k)^2 \tag{3}$$

Where, y is the actual output; Y is the ideal output; T is the number of training samples; M is the number of network layers (excluding the input layer). Weight adjustment formula of output layer:

$$w_{jk}(n+1)=w_{jk}(n)+\eta\Delta\varpi_{jk}+\alpha[w_{jk}(n)-w_{jk}(n-1)] \tag{4}$$

Where, n is the number of iterations; η Is the learning rate; A is the impulse coefficient.

After the network is output, a vector group about y will be obtained. The y1 to y5 in the vector group represent the output values of the neural network of excellent, good, medium, poor and poor respectively. It can be seen from the K-means clustering algorithm that the value of yi in the vector is within [0,1], and the value of yi represents the occupancy of the output area where it is located. The occupancy can be used to determine the level of the bridge safety condition represented by this group of data, and then the score calculation formula of the output network:

$$p=100-\sum_{i=1}^{s}\left\{\left(\frac{\mu_{is}^2-\mu_i^2}{\mu_i}\right)\times y_i\times t_i\right\} \tag{5}$$

In the formula, the value of i is an integer from 1 to 5, and the order also represents the order of yi size. When 1 is the maximum value of yi; Ti represents the interval value of each evaluation interval; μ I represents the width of superior membership function of each evaluation interval; μ Si represents the width of the membership function of each corresponding interval of the output layer.

3.2. Determination of the Index Layer of the Evaluation Model

The selection of main parameters in the safety condition evaluation of long-span SBs has been mentioned in Chapter 3, and optimization judgment and selection of evaluation data have been carried out. It mainly includes the evaluation of the main beam displacement, the main tower displacement, the main beam stress, the main tower stress, the main cable force and the suspender cable force. However, there is another item that cannot be ignored in the bridge monitoring measurement, that is, the change of the structure temperature. The change of the structure temperature includes the temperature change of the main beam and the main tower, which is not only the main factor that causes the temperature load, It is also the verification and correction of the main parameters for the stress of the main beam and the main tower. The proper adjustment and correction of temperature load according to the location environment of the bridge and the climate change of the environment can make the overall safety assessment of the bridge more comprehensive and precise. It is worth mentioning that there is an anemometer in the health monitoring system of long-span SBs, which is mainly used to measure wind load, The data measured by the anemometer are mostly applicable to the specific analysis of the external forces on the main components of the bridge. The assessment model is mainly based on long-term health monitoring and is used to assess the safety status of the bridge, mainly for the overall safety of the bridge structure. Basically, the measured data also includes the impact of wind load on the overall structure of the bridge from outside to inside, Therefore, the temperature load in the environmental load is included in the main indicators of this assessment.

3.3. Processing of Evaluation Data

There are generally two kinds of descriptions of evaluation indicators. The first is a relatively broad qualitative description, and the second is a relatively accurate quantitative description. The first is that when describing a thing, it can only give a framed description of its nature or function, which does not truly reflect the specific characteristics and properties of the thing. However, quantitative description can accurately describe a certain feature of the thing while satisfying the framing display of the thing, which is called "digitalization", so that it can be quantitatively analyzed and studied.

4. Health Assessment of Super Span SBs based on ML

4.1. Health and Safety Status Assessment of Super Span SB

This paper takes the supporting project as an example to evaluate the safety status of the completed SB. In order to study the correlation between various indicators and evaluate the safety status of SBs based on construction quality variation, a certain number of samples need to be selected. However, due to the unique construction process and bridge completion status, it is difficult to obtain large sample data through on-site measurement, and the sample size is too small to ensure the correctness of principal component analysis evaluation.

In this paper, according to the impact of quality variation on the safety of each component during the construction of SBs, according to eight main types of quality variation, anchor settlement deviation, anchor rod deflection angle, main tower longitudinal deflection, main cable damage, main cable erection deviation (main cable rise span ratio), cable clamp deviation, steel box girder weight deviation, welding residual stress, 12 different construction quality variation combination cases are randomly generated. Analyze each case by means of finite element simulation of construction results, and extract six index data of each case. After processing the index value matrix with the principal component analysis method, several main components are obtained. Then calculate the comprehensive score of each case's safety state according to the weight of each main component, compare the case score with the design state, and evaluate the bridge's safety state.

4.2. Selection of Evaluation Indicators

In order to investigate the safety of components, the location of components shall be selected according to the most unfavorable principle, and 1 # long suspender shall be selected as the index evaluation object; The internal force of the main cable at the side of the side span near the 2 # main cable unit is selected to calculate its safety; The stress of the bottom plate of the steel box girder near the maximum bending moment of the tower side is selected to calculate the stress safety degree of the steel box girder; Except for a group of measured data, various construction quality variation values in other cases are randomly generated within the range of measured values or statistical values; In the model analysis, the main tower, main beam and tie rod elements are simulated by beam element, and the main cable and suspender are simulated by cable element; It is assumed that after the construction of SB, the main tower can return to the natural state without the action of unbalanced horizontal force. The construction quality variation parameters of 12 randomly generated cases are shown in Table 1.

Among them, φ C is the anchor settlement value φ T is the deviation value of the main tower, φ N Number of failed wires of main cable, φ F Elevation error of main cable erection, φ M is the deviation angle error of anchor rod, φ D is the deviation of cable clamp, φ G is the weight deviation of steel box girder, φ S is the residual stress of the weld.

According to the variation of construction quality corresponding to each case, calculate the section stress of the main tower, the internal force of the main cable, the internal force of the suspender, the stress of the anchor rod, and the stress of the steel box girder under the bridge completion state in each case. According to the score coefficient matrix and the standardized index data matrix, score according to the two principal components of each case, and then score each case comprehensively according to the variance contribution rate of the components, as shown in Table 2 and Figure 3.

Table 1. Construction quality deviation parameters of each simulation experiment scheme

P	φc/(mm)	φt /(mm)	φn	φf/(mm)	φm/(°)	φd/(mm)	φg/(%)	φs /(MPa)
P1	0	0	0	0	0	0	0	0
P2	10	-10	0	-80	0	5	-2	28
P3	20	10	10	60	0	5	-2	35
P4	0	-15	10	50	0	10	3	22
P5	0	-15	0	-80	0	0	2	26
P6	10	-10	6	50	3	-10	0.5	25

Table 2. Comprehensive score of cases

	SF1	SF2	S
P1	-0.213	1.552	0.363
P2	3.475	-0.412	2.759
P3	1.264	-0.482	0.908
P4	-1.453	-0.458	-1.381
P5	-0.724	-0.271	-0.795
P6	-0.514	0.876	-0.345

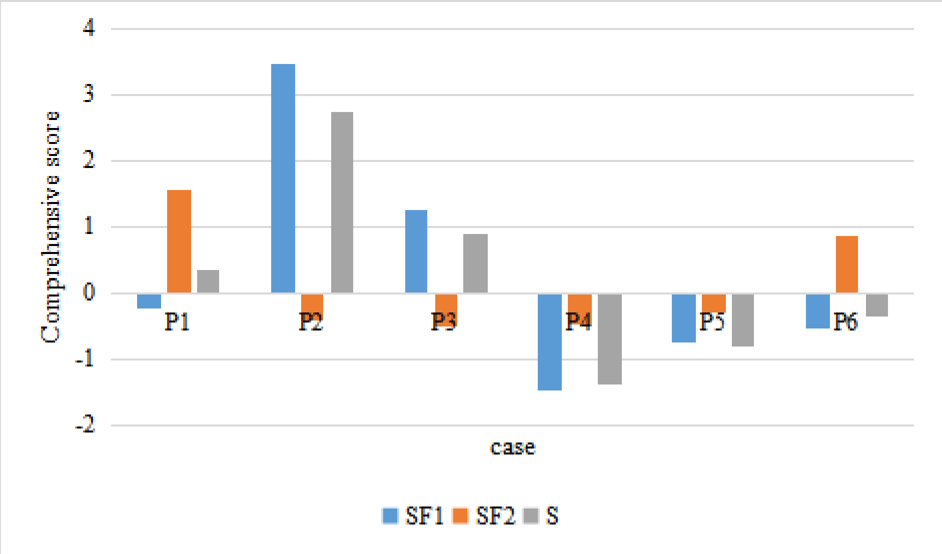

Figure 3. Distribution of comprehensive scores of each case

It can be seen from the chart data that the highest score value is Case P2, SP2=2.759. Case P1 is in the design state, and there is no deviation in the construction quality under the design state, which can be used as the evaluation benchmark for the safety state of the completed bridge. The higher the principal component comprehensive score of the case, the higher its safety. The actual measured construction quality deviation of the project is case P11, whose score is above P1, and the safety degree of the actually constructed bridge is slightly higher than the design state.The feasibility and effectiveness of the health assessment of super long span SBs based on ML analyzed in this paper are verified.

5. Conclusion

Based on ML technology, this paper evaluates the health status of long-span SBs. Through the analysis of the bridge environment and the internal temperature field of the structure, we can understand the changes of the internal temperature field and internal force of the bridge structure with the environment, understand the rules of structural changes in real time, so as to ensure the safe operation of the bridge. The real-time monitoring of the working state of the super long span SB is realized, and the safety of the bridge structure is evaluated. However, this study also has shortcomings. This paper only explores and studies the safety assessment of the completed SB based on the variation of construction quality, and also needs to establish a perfect construction quality control system to develop the construction control from manual calculation, analysis and prediction into a computer control system of automatic monitoring and prediction. After the bridge is completed, the embedded sensors shall be used for remote signal transmission control to form an intelligent monitoring and evaluation of the safety status of the bridge.

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Data Availability

Data sharing is not applicable to this article as no new data were created or analysed in this study.

Conflict of Interest

The author states that this article has no conflict of interest.

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