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Research Article

Fiber Bragg Grating Smart Material and Structural Health Monitoring System Based on Digital Twin Drive

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The damage self-diagnosis function puts forward higher requirements for the research and development of intelligent structural health monitoring, and in most cases, it is necessary to monitor the load first, especially the monitoring of the impact load. The development of smart materials and structures is based on advanced sensing systems. In order to achieve this purpose, a high-speed demodulation system based on fiber grating with double long period grating is studied, and then, a damage self-diagnosis system based on fiber grating is constructed. The system can realize the strain distribution and impact load monitoring of the structure. After quantitative analysis of the signal, an advanced information identification method is used to realize the impact load location. This paper focuses on the data preprocessing process of bridge health monitoring. In view of the characteristics of high data complexity, large amount of data, and many noise components in the process of structural monitoring, this paper adopts basic data cleaning for the original data set, including data dimensionless and missing value processing. Based on the digital twin technology, the composition of the digital twin KNN model of bridge swivel construction monitoring and management is analyzed, and the digital twin system architecture of bridge swivel construction monitoring and management is built. The function display of the monitoring platform, including setting a variety of permission login modes, displaying BIM model, geographic information, and weather environment; monitoring data entry and addition, deletion, and modification; data chart analysis and export; and email warning, to verify the feasibility of the application of digital twin technology in bridge monitoring, and the advantages of the intelligent monitoring system are obtained. The strain error is found to be less than 15.48 $\mu\varepsilon$ in the research, which is within the range of the fiber grating. This method can effectively monitor and forecast these distributed, nonlinear, strongly coupled, multivariable, and time-varying complex structures. By monitoring bridges, the original monitoring data of bridges can be obtained, and scientific research data and analysis services can be provided. In particular, the damage caused by shock and vibration is monitored, so that the accumulation of damage can be detected before it threatens the safety of the structure, so that the damaged structure can be repaired in time to ensure the safe operation of the structure.

1. Introduction

With the development and progress of technology, a complete digital twin system is built from the perspective of bridge swivel construction monitoring and management and interacts with other digital twin systems to realize the interconnection of everything. The digital twin system of bridge swivel construction monitoring and management includes five levels: user domain, digital twin, measurement and control entity, real physical domain, and cross-domain functional entity. Digital twin is a simulation process integrating multidisciplinary, multiphysics, multiscale and multiprobability by making full use of physical model, sensor update, operation history, and other data to complete the mapping of physical entities in virtual space, so as to reflect the whole life cycle process of physical entities.

A structural health monitoring system is an important application direction of intelligent structure, which has attracted more and more people's attention. In the process of bridge swivel construction, monitoring technology is used to ensure the smooth progress of the swivel process and the safety of the swivel construction, and to provide data support for decision-making at each stage. At the same time, it can detect the bridge structure, compare the monitoring data with the previous calculation results, and check each other to ensure the quality of the structure. According to the monitoring results, the design and construction process of the swivel bridge can be optimized. In addition, the data obtained from the construction monitoring can supplement the bridge construction data, improve the bridge life cycle data, and provide an important basis for the later bridge operation and maintenance [1].

In this paper, the sensing model of the uniform period fiber grating and its Fourier transform demodulation theory are studied, and the transmission response characteristics of the uniform period fiber grating are deduced according to the coupled mode theory. In the process of bridge operation, in order to ensure the safety performance and durability of long-span bridges, we need to monitor the health of bridge structures, establish a real-time and smooth network monitoring system, understand the health status of bridge structures, and ensure their normal work and operation. According to the calculation results and monitoring element analysis, sensor model, and using BIM technology, the measurement point layout and early warning mechanism design of the background swivel bridge monitoring scheme are carried out. According to the characteristics of bridges spanning high-speed railways when rotating, a bridge-building comprehensive information model is established. According to the characteristics of the swivel construction of the bridge spanning high-speed railway, combined with the background engineering, the swivel balance system is studied, which is used to adjust the unbalance of the cantilever end during the bridge swivel process, ensure the stability of the swivel process, and improve the construction safety.

2. Related Work

Digital twins are increasingly being introduced into the fields of Internet technology and industrial technology. Fiber Bragg grating (FBG) sensors and extrinsic fiber Fa-Per (EFPI) sensors are two very promising fiber optic sensors in the field of structural health monitoring. Xiaodan designed a virtual training platform for carrier-based aircraft approach and landing based on virtual reality technology. He adopts a distributed architecture, introduces each node of the system in detail, then gives a method for real-time communication using reflective memory technology, and introduces the logical relationship and integration of three dynamic modules [2]. Ye et al.'s accurate assessment of wind characteristics and wind-induced structural responses during typhoons is of great significance for bridge design and safety assessment. He proposed an angular linear approach based on the expectation maximization (EM) algorithm for probabilistic modeling of field-measured wind properties [3]. Sarmadi et al. believe that environmental changes are a major challenge in bridge health monitoring because bridges are more prone to such changes than other civil structures. To address this challenge, they propose a new machine learning approach for early damage detection under environmental changes through clustering, a new damage metric, and an innovative method for selecting an appropriate number of clusters. Estimating reliable alert thresholds is another important challenge for early damage detection by most machine learning methods. On this basis, they propose a new probabilistic method for estimating alarm thresholds using extreme value theory and goodness-of-fit measures. Their major contributions include proposing a new damage metric suitable for clustering-based algorithms for decision making, an innovative cluster selection algorithm for dealing with environmental variability and improving damage detectability, and a new probabilistic method for threshold estimation [4]. Nguyen et al. introduced a new method for diagnosing structural damage based on changes in the mechanical parameters of materials. First, they integrated viscoelastic models into structural damage detection and diagnosis. Therefore, the model defines the mechanical properties of the material by two parameters, the elastic modulus and the coefficient of viscosity. Hooke's model is linear, while viscoelasticity is nonlinear and therefore more accurately reflects reality. Second, they exploited the amplitude and frequency of the vibrational signals and determined their relationship to mechanical parameters that detect structural changes. Based on theoretical analysis and experimental results, their research is more effective and general than previous studies. Simultaneous monitoring of structural changes using different parameters enabled the study to collect more appropriate data compared to previous studies [5]. A structural health monitoring system is one of the important application methods of intelligent structure. The digital twin will have an unignorable impact on the construction industry, and it will become the core engine for the transformation and development of the construction industry. The combination of digital twin and BIM technology will provide a digital model of the city for the government cloud platform based on image scanning, which will cover all high-voltage power grid lines, sewage systems, water supply and drainage systems, highways, traffic control systems, and all interconnected locations in the city. BIM is a building information modeling technology, which is a data-based tool used in engineering design, construction, and management. It is used to describe computer-aided design based on three-dimensional graphics, object-oriented, and architecture.

3. Fiber Bragg Grating Smart Materials and Structural Health Monitoring System Method

3.1. Fiber Bragg Grating Sensor Configuration. The grating sensor refers to a sensor that uses the principle of grating moire to measure displacement. The configuration of fiber Bragg grating sensors can be studied in terms of the number of sensors and the spatial layout of sensors. The spatial distribution of the sensors can adopt various sensor distribution methods such as equidistant distribution, proportional distribution, and mixed distribution, which should be comprehensively determined in combination with various factors such as specific test objects, clamping methods, and loading methods. Therefore, in the subsequent test process, different sensor distribution designs will be adopted for specific test objects.

Regarding the configuration of the number of sensors, the number of sensors that can achieve wavelength division multiplexing for a single channel mainly depends on the bandwidth of the light source and the dynamic range of the measured parameters. Therefore, when determining the number of grating points on a single fiber string, the demodulation limit of the fiber grating demodulator and the actual strain of the measured object should be considered. The specific ideas are as follows.

First, the wavelength variation range of a single grating is calculated according to the strain variation range and grating strain sensitivity of a single grating monitoring point:

$$\Delta\lambda = K_\varepsilon \cdot \varepsilon. \tag{1}$$

In the formula, ε is the strain value of the ith grating point and K_ε is the strain sensitivity of the ith grating point.

Assuming that there are n grating points to be measured on a single-fiber grating string, on this basis, the wavelength variation range of all grating points on the channel of the fiber grating string is calculated [6]:

$$\Delta\lambda = \Delta\lambda_1 + \Delta\lambda_2 + \cdots + \Delta\lambda_n = \sum (K_\varepsilon \cdot \varepsilon). \tag{2}$$

In order to prevent the wavelength signals from aliasing during the measurement of grating points of adjacent wavelengths, the working range of a single grating measured point can be expressed as [7]:

$$\Delta\lambda = K_\varepsilon \cdot \varepsilon + \lambda \tag{3}$$

If n measured grating point on a single-fiber grating string can work normally without wavelength aliasing, then [8]

$$\Delta\lambda = \Delta\lambda_1 + \Delta\lambda_2 + \cdots + \Delta\lambda_n = \sum (K_\varepsilon \cdot \varepsilon + \lambda). \tag{4}$$

Then, the measurement range λ_n of the n sensors is [9]

$$\lambda_n = \Delta\lambda = \sum (K_\varepsilon \cdot \varepsilon + \lambda). \tag{5}$$

If the maximum measurement range of a single channel of the fiber grating demodulator is $\lambda_{\max}$.

$$\lambda_n \le \lambda_{\max}, \tag{6}$$

$$n \le \frac{[\lambda_{\max} - \sum (K_\varepsilon \cdot \varepsilon + \lambda)]}{\lambda_h}. \tag{7}$$

Assuming that the strain range measured by each grating sensor is ε, the above formula can be further simplified as [10]

$$n \le (K_\varepsilon \cdot \varepsilon + \lambda). \tag{8}$$

Therefore, the maximum number of grating sensors that can be connected in series on each channel of the fiber grating demodulator can be calculated by the above formula [11].

3.2. KNN Algorithm. The mechanism of the KNN algorithm applied to the analysis of bridge monitoring data can be summarized as follows: when the model obtains a new detection data sample point, KNN can classify it according to the nearest known sample points of the sample point. Due to such classification characteristics, this paper uses this as a theoretical basis to design a bridge loss judgment model to classify the monitoring data of the bridge, so as to indicate the monitoring data of the bridge in a healthy state and a damaged state [12].

The basic steps of the KNN algorithm:

Input data set:

$$T = \{(x_1, y_1), (x_2, y_2), (x_3, y_3), \cdots, (x_n, y_n)\}, \tag{9}$$

where x_n represents a feature vector of the instance [13].

Output: the category to which instance x belongs.

According to the selected distance metric formula, find the k instance points closest to x in the data set, and the set of these K points is called the k neighborhood $N(x)$ of x.

According to the classification rule in the k neighborhood of x, the majority votes the classification category y of x:

$$y = \mathrm{argmax}_c \sum x \in N(x) I(y = c). \tag{10}$$

In the above formula, I is the indicator function, that is, when $y = c$, $I = 1$; otherwise, it is 0 [14].

At time t, the input layer inputs the bridge high-finesse time series data, and the state of each unit of the input layer at this time [15]:

$$U(t) = [u_1(t), u_2(t), \cdots, u_m(t)]^T. \tag{11}$$

When new data is input, the algorithm will update the state $x(t)$ of the storage layer and the update rule [16]:

$$x(t+1) = wx(t) + w^{\mathrm{in}} u(t+1). \tag{12}$$

After the node state update of the storage layer is completed, the node state matrix is obtained [17]

$$y = f^{\mathrm{out}} \left(\int w^{\mathrm{out}}(t) dt \right), \tag{13}$$

where w^{out} is the weight matrix of the output layer, and f^{out} is the activation function of the output layer.

Let

$$\begin{aligned} K_1 &= \frac{L_0}{L_1}, \\ K_2 &= \frac{A_0}{A_1}. \end{aligned} \tag{14}$$

It can get [18]

$$\varphi_1 = \frac{K_1 K_2}{K_1 + K_2 - 1}, \qquad \varphi_0 = K_\varphi \varphi_0. \tag{15}$$

Bridge construction monitoring is a general term for all the work that provides technical support for the realization of bridge design requirements through construction process simulation analysis, on-site monitoring and error identification and prediction, and feedback control. Bridge construction monitoring should include monitoring calculation, construction monitoring and data analysis, and feedback mechanism. The monitoring calculation includes design compliance calculation, presimulation calculation, and real-time simulation calculation. Construction monitoring includes stress (internal force) monitoring, linear monitoring, temperature monitoring, and monitoring of necessary environmental factors.

3.3. Structural Design of Digital Twin Bridge Health Structure Safety Monitoring System. The digital twin bridge health structure safety monitoring system roughly includes two parts:

(1) Sensor and demodulation equipment system: sensors are divided into preembedded sensors from the installation stage, such as concrete embedded strain gauges, embedded crack gauges, and earth pressure gauges. Surface sensors, such as beam surface strain sensors, expansion joint displacement sensors, accelerometers, and inclinometers, were used. The demodulation equipment system is basically divided into static and dynamic monitoring. The static monitoring is second-level monitoring, which is collected at a certain interval, and the dynamic monitoring is about 100 Hz, the vibration data of the bridge is collected in real time

(2) Monitoring center system: the monitoring center is mainly to improve the efficiency, scientificity, rationality, and traceability of management, to achieve rational allocation of resources, and to reduce human errors. The system can be divided into two parts, data acquisition and transmission system and system integration. The data acquisition and transmission system integrates the sensor data in a unified manner, collects it centrally, and completes the software protocol connection with the system integration system. The system integration system is mainly used to assist the bridge management center, which roughly includes the following functional modules, manual inspection and maintenance management module, comprehensive early warning safety assessment module, and management center database management module

3.4. Hardware System Design of Digital Twin Bridge Health Structure Safety Monitoring System. The hardware part of the digital twin bridge health structure safety monitoring system mainly consists of three parts:

(1) Sensor system: it consists of sensors with various functions and special components distributed on the bridge structure. The sensors are divided into embedded sensors and surface-mounted sensors

(2) Data acquisition system: the data acquisition system is divided into data acquisition and auxiliary devices. The data acquisition system is composed of demodulation equipment, acquisition equipment, acquisition computer, sensor optical cable, cable network, etc., which are arranged inside the bridge junction or on the bridge deck. At present, there are about a dozen types of sensors, and it also indicates that there are more than a dozen different types of demodulators. The auxiliary system consists of the equipment in the field and the monitoring center to assist the normal operation of the above system, including the cabinet, the chassis, the power supply module, the uninterruptible power supply system, and the lightning protection system

(3) Data processing system: process various sensors into digital signals for easy identification, package data, and connect to the system integration module. The hardware system design of the digital twin bridge health structure safety monitoring system is shown in Figure 1

3.5. Software Module Design of Digital Twin Bridge Health Structure Safety Monitoring System. The overall architecture diagram of the software part of the digital twin bridge health structure safety monitoring system mainly covers the following contents:

(1) The sensor data acquisition, protocol transmission, and other related support services involved in each sensor measurement subsystem

(2) The centralized acquisition function of each sensor subsystem

(3) The relationship between the central database subsystem and other systems and the flow of related data

(4) The functional connection between the user interface subsystem, the structural warning and evaluation subsystem, the manual inspection auxiliary subsystem, and the user terminal. The system of the digital twin bridge health structure safety monitoring system software is shown in Figure 2

3.6. Bonding Process of Fiber Grating Sensor and Measured Structure. The surface-mount packaging method is usually based on the preset optical fiber sensing layout, and the corresponding fiber grating sensing points are arranged on the surface of the monitored point of the structure, and the grating sensor is fixed with the help of a protective adhesive layer. The operation is convenient and simple, and it will not destroy the initial structural state of the measured object and will not cause too much influence on the strain transmission efficiency and sensitivity of the fiber grating sensor. In the actual

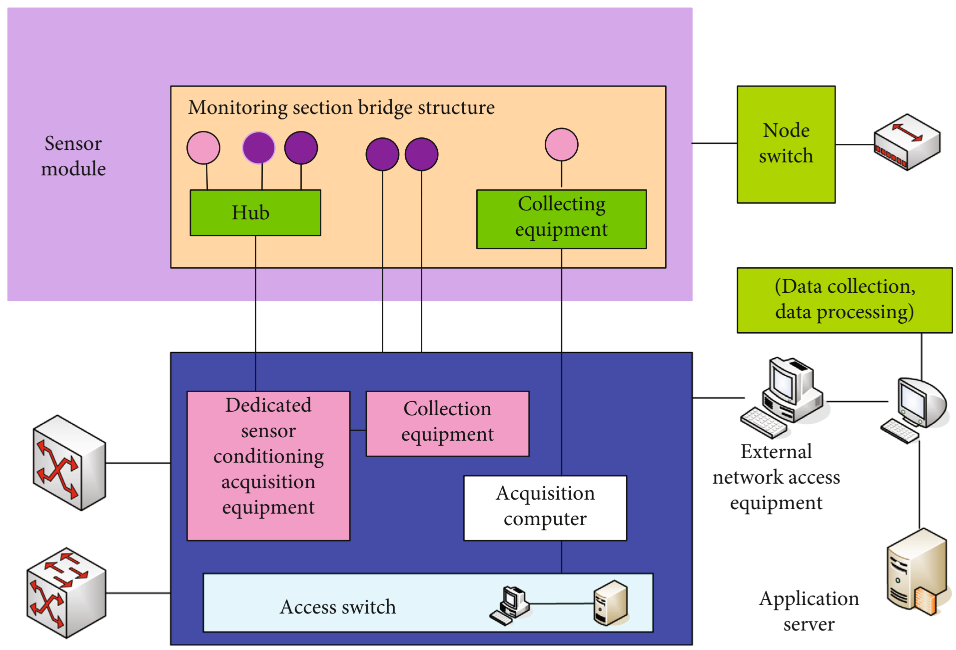

Figure 1: Hardware system design of digital twin bridge health structure safety monitoring system.

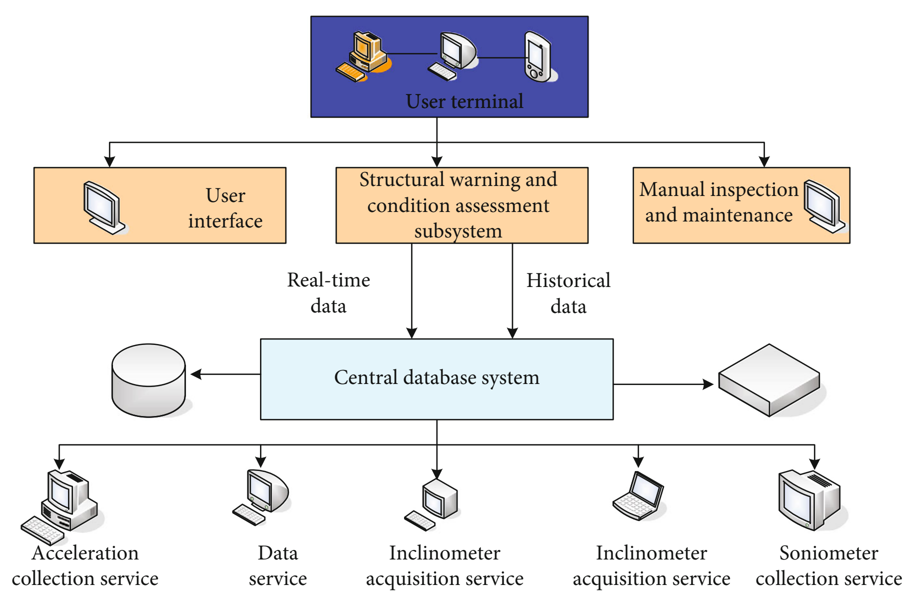

Figure 2: Software modules of the digital twin bridge health and structural safety monitoring system.

operation process, on the one hand, it is necessary to select an appropriate bonding method to fix the fiber grating to ensure its fit with the monitored point on the surface of the structure, and at the same time to protect the fiber grating from being damaged. On the other hand, it is necessary to select a reasonable amount of bonding material to reduce the influence on the strain transfer efficiency of the sensor after the fiber grating sensor is bonded to the structure. Based on the above discussion, the bonding process of the fiber grating sensor and the structure can be carried out according to the following steps: first, according to the preset optical fiber hybrid multiplexing network, the number and layout of the sensors required for the test are planned. Grating sensors with different center wavelengths are selected and connected in series to form a fiber grating string, the connection is spliced by an optical fiber fusion splicer, and a metal sleeve is added at the fusion connection to protect the fusion point from breaking. Secondly, in order to ensure more sufficient contact between the grating sensor grid area and the structure, the grating sensor with the coating layer removed is selected, the grating grid area is laid on the monitored point corresponding to the structure, and a certain prestress is preapplied before gluing, to remove the residual stress that may be introduced in the process of fabrication and coating layer filtering in the grating gate

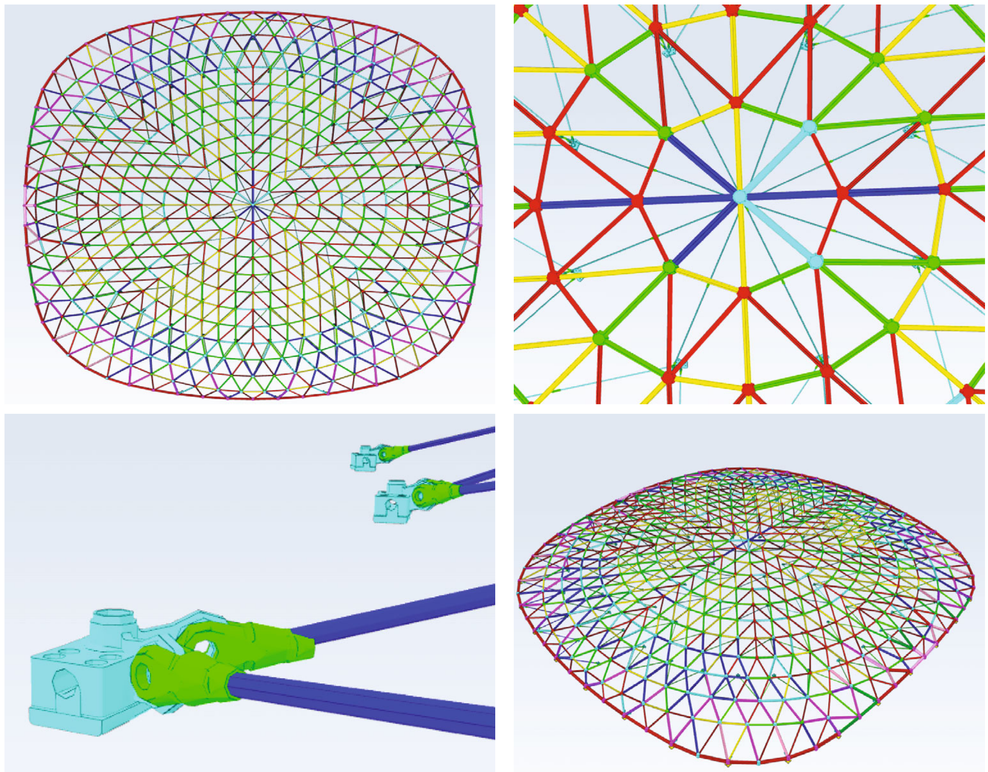

Figure 3: Application scene of digital twin of Hebei North University Gymnasium (the picture comes from the author's own drawing).

region. The gate area is preliminarily fixed by using a curing adhesive, and the bubbles that may be generated by the adhesive layer are extruded to ensure that the gate area and the surface of the structure are fully attached. Again, after the cured adhesive layer is air-dried (about 1 h), epoxy resin is applied to the fixed part of the gate area. Its purpose is to shield the crosstalk caused by external stress and, at the same time, protect the cured adhesive on the inside from the influence of the external corrosive environment. Finally, after all the adhesive layers are fully cured (about 24 h), follow-up tests are carried out. Since the strain transfer efficiency of the grating sensor is closely related to the properties of the adhesive layer, during the bonding process, the adhesive layer should be smeared evenly and the thickness is moderate to reduce the influence of the adhesive layer on the strain transfer efficiency of the sensor. Based on the above discussions on sensor network layout, sensor configuration, sensor bonding method, etc., the sensor system and structure integration are designed. For example, the digital twin application scenario of Hebei North University Gymnasium is shown in Figure 3.

3.7. Quality Control Measures in the Installation Stage of Embedded Sensors

(1) The on-site organization is as follows:

Because the sensor preembedding stage needs to follow the bridge construction progress, it has high construction requirements, which can neither delay the normal construction period nor affect the installation quality. The flow-type construction method is adopted, combined with the parallel construction method to speed up the progress when necessary, that is, the work flow of forecasting installation in advance, compact installation process, and quick departure after installation. Since the sensor is installed in stages with the progress of the bridge construction, the bridge construction unit should be reported to the bridge construction unit 3 days before the installation is required, and the preparations before the installation should be done. The installation process should be compact and regular, and the installation should be carried out when the construction and installation team changes shifts as much as possible. After installation, only the engineer who recorded the installation data is left, and the rest can leave the site to ensure that the progress of the bridge construction is not affected.

(2) To control the installation quality, first of all, we can classify all the sensors that need to be embedded and installed according to the installation location according to the needs of the project. The area is divided according to the range of 500 meters, and a technical support person from a fiber grating sensor supplier company is arranged for each area to conduct real-time technical control. The main points of control are as follows:

(a) Recording the wavelength data of the fiber grating sensor in real time (monitor the initial value)

(b) Compiling record files of fiber grating sensor burial, including points, on-site pictures, sensor types, etc.

(c) Marking and recording the position of the optical fiber outgoing fiber, and report it to the construction unit, emphasizing that the optical cable should not be broken or buried in the later bridge construction process

(3) The main task of the construction team is to carry out the equipment according to the requirements of the technical personnel of the equipment supply company, which are classified into:

(a) Preparatory work before burying such as drilling and binding

(b) The sensor is buried

(c) Cable and traction of optical cable

The formula for covariance is as follows [19]:

$$X_F(X, Y) = E\left[(X - u_x)\left(X - u_y\right)\right], \tag{16}$$

where X and Y represent two random variables.

Data anomalies in bridge health monitoring belong to time series anomalies, that is, data anomalies are related to time. If the value of a subsequence in the time series deviates greatly from the values of other parts, and such deviation is not generated randomly, but in a way that is completely different from other subsequences, that is, this subsequence may be an abnormal subsequence. There are mainly three types of anomalies in bridge data: point anomaly, pattern anomaly, and sequence anomaly. A general point anomaly refers to a data point whose data value at a certain time point is significantly different from the threshold or abrupt change caused by the degradation of sensor performance or the mutation of external influence factors. The pattern anomaly refers to the existence of small continuous anomalies in the data sequence of a sensor. Such anomalies mostly occur when the sensor fails during continuous acquisition or the transmission line has faults, or it may be an anomaly displayed by obvious changes in the data caused by the gradual aging of the bridge, and there is a significant pattern difference with the continuous data in other time periods. Point exceptions can be thought of as pattern exceptions of length 1. Sequence anomaly is a time series that is significantly different from other time series and originates from different mechanisms. For eigenvalue decomposition,

$$A\eta = \lambda\eta, \tag{17}$$

$$A = Q\sum Q^{-1}. \tag{18}$$

The wave formula for light waves propagating in an optical fiber [20]:

$$\nabla^2 E + KNE + \nabla^2\left(E \cdot \frac{\nabla\varepsilon}{\varepsilon}\right) = 0, \tag{19}$$

Table 1: Corresponding strain errors.

Actual strain ($\mu\varepsilon$)	Wavelength change (nm)	Sensitivity relative error (%)	Strain error ($\mu\varepsilon$)
100	0.12	0.008	0.08
1000	1.2	0.077	0.77
10000	12	0.774	7.74
20000	24	1.548	15.48

$$\nabla^2 h + KNh + \nabla^2\left(h \cdot \frac{\nabla\varepsilon}{\varepsilon}\right) = 0, \tag{20}$$

where E, h are the electric field strength and the magnetic field strength.

4. Health Monitoring System Results

Taking the initial center wavelength of the fiber grating as 1550 nm, its strain sensitivity is 1.2 pm/$\mu\varepsilon$. Assuming that the actual strains generated are 100, 1000, and 10000, the corresponding strain errors are shown in Table 1. It can be seen from Table 1 that within the range of the fiber grating, the strain error is also within 15.48 $\mu\varepsilon$, that is, the influence of the center wavelength change of the fiber grating on the strain sensitivity coefficient is extremely small, which can be completely ignored in engineering applications.

According to the introduction of the sensitivity adjustment principle of the sensor, the sensitivity of the cable force sensor is affected by its main key parameters $K1$ and $K2$. The two parameters $K1$ and $K2$ have the same trend of influence on sensitivity and the same degree of influence [21, 22]. Among them, when the two parameters of $K1$ and $K2$ are in the range of 0-10, respectively, the sensitivity changes more sharply. After more than 10, the sensitivity change tends to be gentle with the increase of the parameters. Therefore, we are designing the variable diameter part of the sensor, considering that the two parameters of $K1$ and $K2$ are controlled within 10. The effect of sensor parameters on sensitivity is shown in Figure 4.

The analysis model is used to analyze the accident, find the cause of the accident, and predict and analyze the technical performance of the bridge project. Combining BIM technology with finite element technology, the bridge structure and the key parts of the bridge structure can be analyzed by finite element, and the safety of the structure can be monitored and evaluated. Combining BIM technology with finite element technology is shown in Figure 5.

When the monitoring result finds that the single pile load reaches 95% of the allowable value, the system will alarm, and the platform operator must stop the operation of the bridge and conduct an appropriate load shedding test on the area of the bridge until the alarm is cancelled and then gradually resume the bridge operation. The bridge column loads and alarm indicators are shown in Table 2.

According to various problems in the commissioning stage of the digital twin bridge health structure safety monitoring system, the site is investigated and probability statistics are

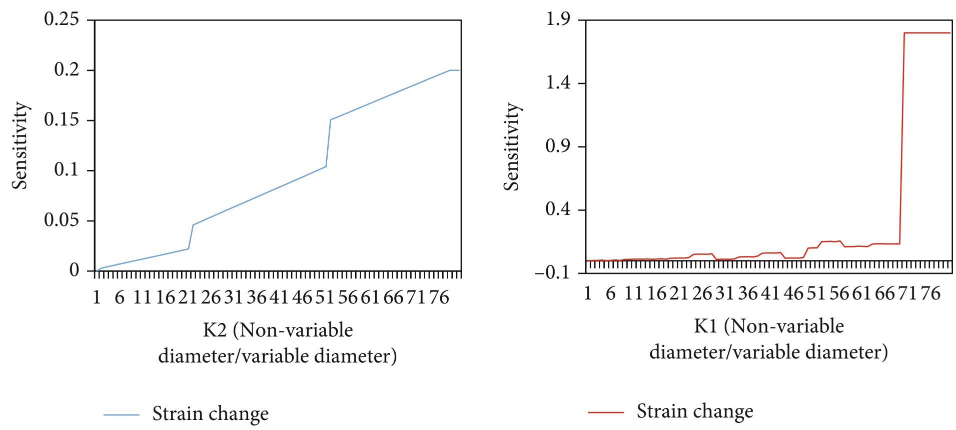

Figure 4: Effect of sensor parameters on sensitivity.

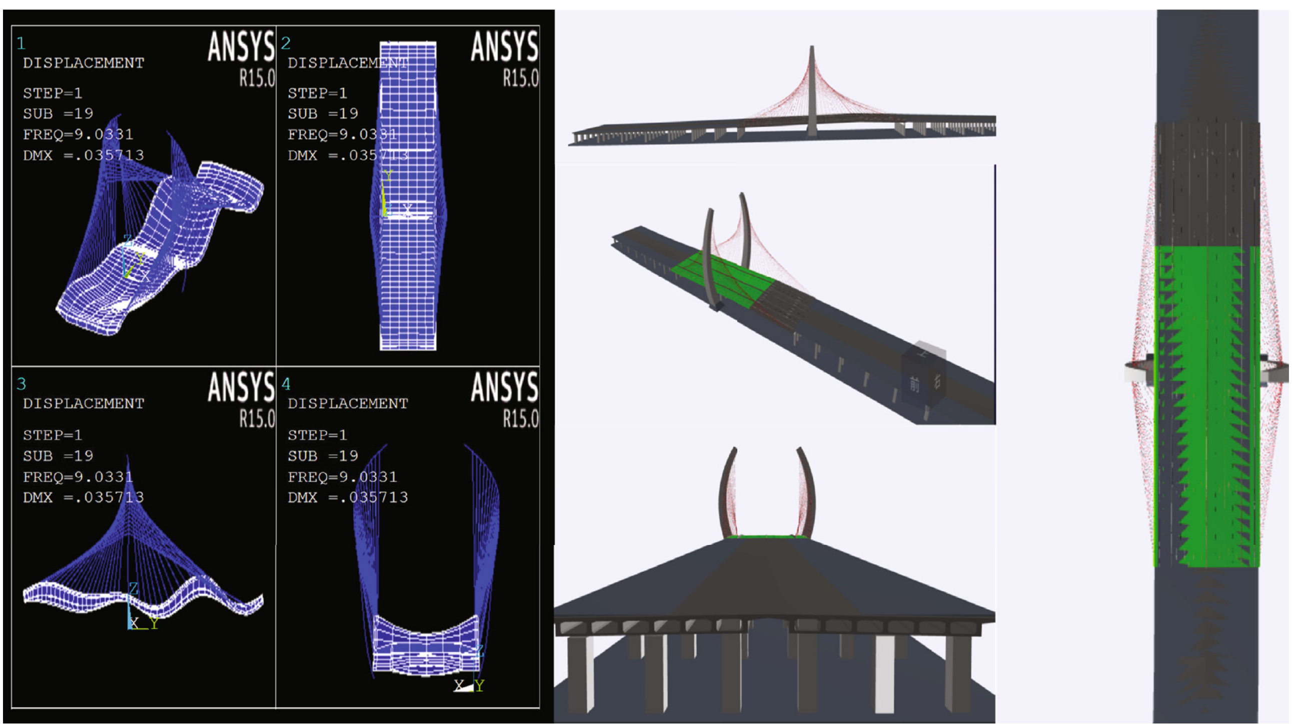

Figure 5: Combining BIM technology with finite element technology (the picture comes from the author's own drawing).

carried out, and the defects and frequencies are found in Table 3.

After adopting the standard data protocol, some manufacturers of niche products, such as fiber grating equipment suppliers, have difficulty in clear data protocol, difficult development, and problems in data debugging after development [23]. The problems of fiber grating equipment are shown in Table 4.

Under the two excitation methods, the accuracy rate of KNN varies with the K value. In the environmental excitation data set, the accuracy rate will gradually increase with the increase of the K value. When the K value is about 210, the accuracy rate reaches the highest 99.95%. When the K value continues to increase, the accuracy rate will slowly decrease with the increase of the K value, and the overall change is not large. Therefore, on the environmental excitation data set, when the K value is set to 180, the accuracy rate is the

Table 2: Bridge column loads and alarm indicators.

Part of the bridge column serial number	Carrying capacity	Current stigma force (kN)	Residual stigma force (kN)
1	2059.07	1028.78	1030.88
2	2152.83	1171.35	981.67
3	2101.95	1435.43	666.45
4	2065.70	1046.76	1019.89

Table 3: Defects detected and frequency.

Project	Frequency	Cumulative frequency (%)
Sensor point data record error during installation	28	39.4
Repeated communication times of various data protocols	21	68
Repeatedly modify the system integration warning value settings	16	92.5
The data does not meet the standardization requirements	6	100

Table 4: Fiber Bragg grating equipment issues.

Project	Frequency	Cumulative frequency (%)
Manufacturer's data protocol development time is long	26	44.9
Data transmission is unstable after development and debugging	20	79.3
Industry differences are large, and it is difficult to connect	7	91.4
The manufacturer has other work arrangements and the new work content is not in place	5	100

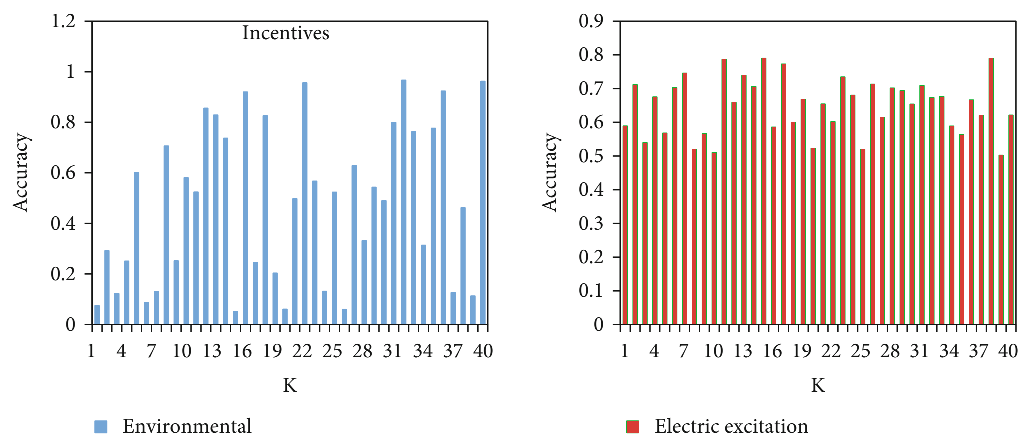

Figure 6: KNN parameter adjustment results in the environmental and electric excitation data sets.

highest and the evaluation result is the best. The parameter adjustment results of KNN in the environmental and electric excitation data sets are shown in Figure 6.

Acceleration sensor data were collected for a total of 12 days, and the sampling frequency of acceleration information was 100 Hz, which showed the process of bridge condition from healthy to damaged. The research center increased the number of accelerometers to monitor the acceleration information of the bridge structure again from 8.7 to 8.10. The acceleration sampling information on August 7 was 32 Hz, and the sampling information on 8.8-8.10 was 20 Hz. Some sampling dates and sampling frequencies are shown in Table 5.

In the experiment of single-variable pattern anomaly detection based on KNN distance, the compressed segmentation of the data sequence is first done. For the convenience of operation, the method uses the data in the form of text derived from the database. The selected data of each sensor is controlled at about 8000 data values.

First, taking deflection sensor data as an example, the fitting degree of the time series formed by the original data and the time series after segmentation is shown in Figure 7. When the segmentation error in the segmentation algorithm is set to 0.8 d, the number of original data is 8597, and the data after compression is 1860, so the compression ratio is about 21.7%. At this time, the data before and after the segmentation can basically match, and the compression segmentation error can be adjusted reasonably according to the calculation requirements. The smaller the error, the closer to the original sequence, and the more data values.

Table 5: Some sampling dates and sampling frequencies.

Date of data collection	Sampling frequency	Assessment of damage status
2018.1.1	100 Hz	Healthy
2018.5.5	100 Hz	Minor injury
2018.7.31	100 Hz	Severe injury

The data set records the real-time linear acceleration response of the bridge at 4:20 p.m. local time on June 12, 2018 and the component changes of the gravitational acceleration in all directions. The acceleration time thread is shown in Figure 8.

The silhouette coefficients corresponding to different numbers of clusters, in general, with the increase of the number of clusters, the silhouette coefficient has a downward trend,

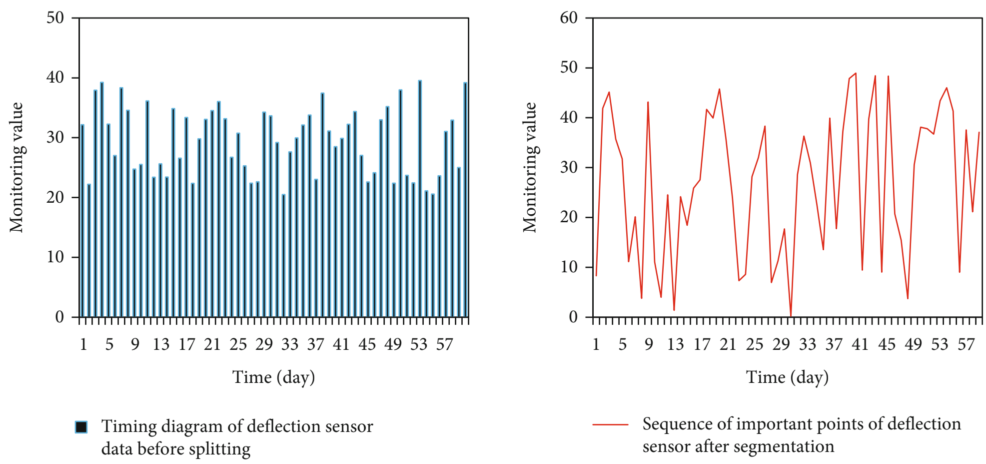

FIGURE 7: The fit of the time series formed from the original data and the time series after segmentation.

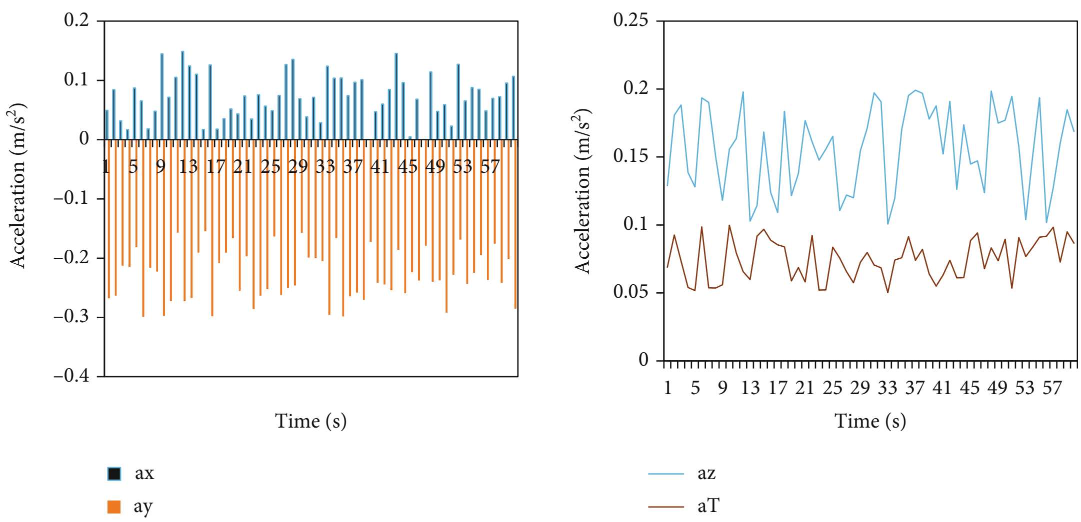

FIGURE 8: Acceleration time thread.

but this does not mean that the fewer the number of clusters, the better. Because with the increase of the number of clusters, the difficulty of model learning gradually increases, and the corresponding silhouette coefficient will decrease accordingly. The contour coefficients are set as shown in Table 6.

The initial value of K of the KNN model is set to 3, that is, the judgment of the new data point is based on the categories of the 3 "nearest neighbors" closest to it. When $K = 3$, the accuracy of the model on the training set is 95.31%, and the accuracy on the test set reaches 91.63%. Its ROC curve is shown in Figure 9, and the AUC area reaches 0.982.

TABLE 6: Profile factor settings.

Number of clusters	Silhouette score (silhouette score)
2	0.1932
4	0.1712
5	0.1655

5. Discussion

The main components of the bridge monitoring system are as follows: data acquisition module, data transmission module, data analysis and processing module, data management module, and user interface module. The data acquisition module is the bottom part of the whole monitoring system. According to the characteristics of different bridges, the types and quantities of sensors used are different. The data transmission module uses a network constructed by a large number of hubs and routers to transmit the sensor signal data to the monitoring center. The data processing and analysis module preprocesses the data, eliminates data noise and data anomalies, and uses data analysis software to analyze and diagnose bridge health data for damage, the degree and location of damage, pay attention to and study the overall behavior and structural state changes of bridges, and the long-term development trend of bridge bearing capacity and durability. The data management module manages all related bridge structure information, health status monitoring information,

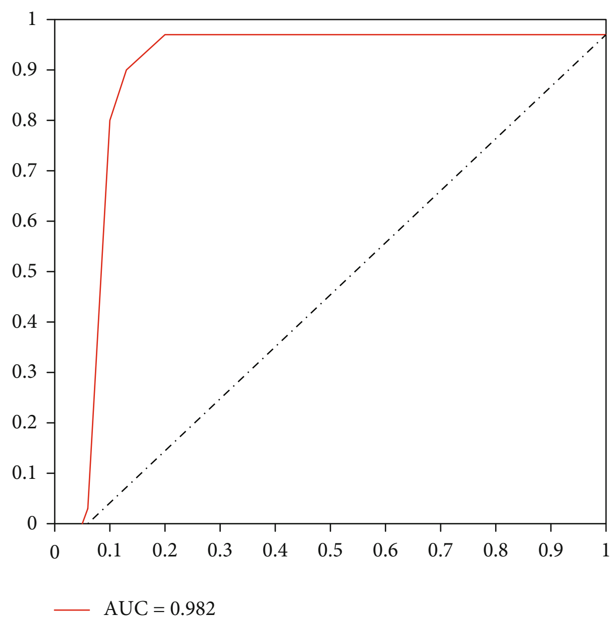

Figure 9: ROC curve.

data processing, and analysis results of the entire bridge. The user interface module presents the bridge-related information to the relevant staff through the visualization program.

The modern spatial structure is developing towards a large and complex direction. These large structures such as space shuttles, high-rise structures, new bridges, and long-span grid structures will be affected by design loads and various unexpected external factors (foreign object shock, vibration, earthquake, explosion, etc.) in complex service environments, and the severe vibration or shock can cause structural damage to varying degrees. The designed service life of large bridge structures can generally reach about one hundred years, and the working life of most bridges needs to last for decades or even hundreds of years. During the service period of bridges, different types of structural damages occur to bridges due to environmental factors, load states, human activity factors, performance variations of building materials, and natural disasters. When the damage accumulates to a certain extent, the accident of sudden structural damage will occur, and the safety of people's lives and properties will be greatly threatened, resulting in significant economic losses. There are many reasons for bridge accidents: engineering quality problems, insufficient postmaintenance of bridges, bridge damage, and functional degradation caused by natural causes, etc.

The traditional bridge monitoring technology generally conducts manual testing under the condition of interrupting bridge traffic. Through regular and nonregular onsite inspection and testing, the actual data is obtained and the test results are obtained by calculation and analysis. The traditional method is limited by time, manpower, measurement conditions, etc., cannot timely feedback evaluation results, is inefficient, has discontinuity, and needs to rely on engineers with rich experience. At the same time, the data collected by traditional methods are relatively not timely enough, are intermittent, and cannot fully and truly reflect the health status of bridges.

The application of BIM in the construction stage realizes the combination of personnel, machinery, materials, documents, etc. with the BIM model in construction, which makes the project schedule easy to control and adjust, improve project quality, control construction safety, and save construction costs. In the process of rotating construction, although the bridge is in a statically indeterminate cantilever state and the force is simple, the bridge is in a state of motion and force when it rotates, and it may be subject to unmeasurable and uncontrollable factors such as wind load, temperature, traction, and friction when it rotates. Therefore, it is necessary to carry out strict construction monitoring on the construction safety and quality of this stage, so as to avoid the phenomenon that the bridge cannot rotate normally or even the bridge overturns during the rotation.

Based on the application of the above BIM technology, more in-depth application research can be carried out on some information, such as regular inspection and rating, preventive screening technology, etc. For example, in the later operation and maintenance of bridges, the operation and maintenance information is transmitted to the BIM model information resource library to realize the transmission of model, coding, data, and file information from the construction period to the operation period, and carry out the whole process management of data monitoring, technical evaluation, comparison and tracking, and auxiliary decision-making.

BIM is widely used in construction, and it can simulate construction plans, carry out special construction, and make construction disclosures. Digital photogrammetry and panoramic technology are used to quickly obtain the original and real-time image data of the project, establish a panoramic system during the construction period, monitor the construction progress, facilitate onsite online management and project live query, and compare and analyze the planned and actual construction. Managing materials, construction data, responsible persons, etc., check the hidden dangers of construction quality and safety, and ensure construction quality and safety. Associating drawings with components, automatically nesting materials, using cloud technology for dimensional inspection, and combining 3D laser scanning to obtain 3D deviation values for the production and design of each component, assisting component quality control, and accurately controlling construction, etc.

Based on Web and digital twin technology, the research on monitoring and management of bridge swivel is carried out. The B/S architecture is used to build a bridge swivel monitoring platform, which integrates animation, BIM model, pictures, and monitoring data into the same interface. Digital twin technology is used to establish a five-dimensional model (physical bridge, virtual bridge model, connection, twin data, and application service) for monitoring and management of bridge swivel construction across high-speed railways and build a digital twin system architecture based on bridge swivel construction monitoring and management. Combined with the background engineering, the operation feasibility of the digital twin system is demonstrated, and the intelligent and automatic management of bridge rotation monitoring and control is realized.

The real swivel bridge and the virtual bridge exchange data through the twin data platform, and the twin data two-way drive the real swivel bridge object and the virtual swivel bridge. The twin data it contains include real-time monitoring data, computational simulation data, rotating body precontrol data, error analysis data, regulation rule data, feedback control data, and personnel construction management data. The monitoring data obtained by the monitoring sensors of the real bridge is transmitted to the virtual bridge through the digital twin platform to simulate the real bridge state and perform real-time monitoring and calculation simulation. The feedback control data generated in the virtual bridge is transmitted to the real bridge through the digital twin platform to control the construction of the bridge swivel. Judging from the operation of the current bridge health monitoring system, the difficulty is often not the collection of monitoring data, but how to process the massive monitoring data accumulated over time, extract the health status information of the bridge with effective data processing and analysis methods, and diagnose and evaluate the bridge. In various monitoring systems, the data processing module is usually the core component. Whether it is damage identification, safety assessment, or change prediction, only good data processing and analysis methods can ensure the meaning and value of the system [24].

6. Conclusion

Aiming at the inconsistency in the dimension of structural output response information and the time-consuming data analysis, this paper uses KNN to extract effective data features, thereby reducing the computational complexity of the algorithm and greatly reducing the learning difficulty of the damage assessment model, improving the accuracy and efficiency of evaluating models. Combined with the work content of swivel construction monitoring, a bridge swivel construction monitoring system is established, the composition and mutual relationship of the monitoring system are analyzed, and the partial composition of the system is reflected in combination with engineering examples. In this paper, design check calculation, monitoring prediction calculation, and key structural analysis are carried out for the background engineering, and the monitoring elements are analyzed for the calculation results of the swivel bridge. This paper proposes to establish a monitoring sensor family library and establish a representative monitoring sensor BIM model according to the monitoring requirements. In the field of engineering, the application of BIM technology should be further explored, such as digital twin reverse modeling technology and automatic identification technology of safety hazards.

Data Availability

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

Conflicts of Interest

The authors state that this article has no conflict of interest.

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