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A decision-making system for large span bridge inspection intervals based on sliding window DFNN

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Abstract

To avoid expert inspection, this study develops a decision-making system for large-span bridge inspection intervals based on dynamic fuzzy neural networks (DFNN), which can find knowledge from existing inspection data. A sliding window is introduced to enable the system to learn incrementally so that the system can update along with the bridge degradation. Tsing Ma Bridge is adopted as a prototype bridge while its rating system established based on the fuzzy-analytic hierarchical process (Fuzzy-AHP) method is employed to generate training and testing samples. The capability of the system in finding the relationship between the rating indexes and the rating scores as well as renewing itself with the bridge degradation is then verified. And the influence of the length of the window is investigated. The research shows that the method can make accurate decisions for bridge inspection intervals after being trained by existing data.

Keywords: Bridge inspection, Dynamic fuzzy neural network, Sliding window, Incremental learning

1 Introduction

Deterioration accumulation is inevitable during bridges' service life due to harsh environments including overloading, earthquakes, temperature, corrosion and so on. To ensure bridges' serviceability, durability, and safety, inspecting in-service bridges in time is essential. After the inspection, appropriate maintenance measures can be adopted to ensure the normal operation of the bridges, which lays foundation for the development of the society. For arranging inspection work reasonably, the Chinese codes (JTG H11-2004, JTG/T H21-2011) suggest initial inspection, daily inspection, routine inspection, periodic inspection, and special inspection for bridges. Among them, regular and periodic inspections rely on visual inspection. Special inspection includes on-site testing, verification, and analysis about the states of the components, and is performed only when further diagnosis about the causes of the damages, damage degrees is needed, or when bridges are catastrophically damaged. In the United States, there are different types of bridge inspections: initial inspection, routine inspection, in-depth inspection, fracture critical inspection, and special inspection (Hearn 2007). According to the codes, the decision of the inspection intervals relies more on the engineers' experience.

To reasonably determine the interval between two adjacent inspections, evaluating the current states of bridges is necessary. The analytic hierarchy process (AHP) method is the basis of the Chinese specifications (JTG H11-2004, JTG/T H21-2011) and many bridge evaluation systems (Huang et al. 2007; Li et al. 2016). According to the method, inspectors need to score the severity of each bridge disease based on visual or instrument detection results, and then weight the scores to evaluate the states of the bridge. In the process, the weights for each component and disease need to be obtained through experts' investigation. But as the investigation is time consuming, the weights are difficult to be adjusted in time to reflect the changes in the importance of the indexes, which caused by bridge degradation (Xu et al. 2018). At the same time, the inspector's subjective description for the degree of the damages will lead to uncertainty in the evaluation results (Anoop et al. 2012; Campbell et al. 2021).

In order to overcome the above difficulties, Sasmal and Ramanjaneyulu (2008), Liang et al. (2001) and Liu et al. (2017) introduced fuzzy theory to deal with fuzzy information such as subjective judgment from inspectors. Lan (Lan and Shi 2001) and Xu et al. (2018) introduced the variable weight theory to adjust the weights for the indexes. Wang et al. (2008) and Yang et al. (2019) used the evidence theory to fuse multi-source information to evaluate bridges condition. Cattan et al. (1997) used artificial neural networks (ANN) to map bridge geometric and structural parameters to structural states. Kushide et al. (1997) developed an expert system for concrete bridge inspection via ANN. Li et al. (2011) constructed a bridge component importance and vulnerability assessment system based on the fuzzy analytic hierarchy process (F-AHP) (Wong 2006). The system considers both the monitoring data from the structural health monitoring (SHM) system and the visual inspection results in determining inspection intervals for different components of the Tsing Ma Bridge. To solve the uncertainties caused by environmental factors and subjective evaluation, Xu et al. (2023) proposed a bridge component evaluation system based on cloud-analytic hierarchy process (C-AHP) by combining cloud theory with AHP. However, the weights of the indexes in the systems proposed in the above researches still depend on experts' investigation.

This paper proposes a decision-making system for long-span bridge inspection intervals based on dynamic fuzzy neural networks (DFNN), which can find the weights of the indexes from existing bridge inspection data. Nevertheless, the traditional DFNN learning algorithm relies on a fixed sample library. To update the sample library according to accumulating inspection data, a sliding window is introduced to improve the learning algorithm and make the system have incremental learning capability. Finally, the method is used to make decisions for the inspection intervals of some components of the Tsing Ma Bridge, and the effect of the sliding window length is discussed.

2 DFNN for bridge inspection intervals

2.1 DFNN combining inspection process

It is difficult for inspectors to apply clear quantitative criteria to determine the severity of bridge damages, which means that the severity is fuzzy. Zadeh et al. (1996) proposed fuzzy theory that quantifies fuzzy concepts using fuzzy sets and affiliation functions to provide a mathematical description for fuzziness. Fuzzy inference system (Takagi and Sugeno 1985) is one of the branches of fuzzy theory, which simulates complex systems by dividing the input variable space into several fuzzy sets and combining them to establish fuzzy rules. A fuzzy inference system is essentially an expert system based on fuzzy rules, which are expressions of expert experience, and the Takagi-Sugeno-Kang (TSK) model is one of the most adopted models to establish the rules. The output of each fuzzy rule in the TSK model is a linear combination of the affiliation degrees of the input variables to different fuzzy sets. Theoretically, a fuzzy inference system with a reasonable structure can approximate any continuous or discrete mathematical function with arbitrary accuracy.

However, for complex bridge structures, there is no clear basis for choosing the structure of a fuzzy inference system, which including the selection of the fuzzy sets, affiliation functions, and fuzzy rules. The state of a bridge component is influenced by a variety of factors, and its evaluation system is a typical multi-input system. Since the number of fuzzy rules in traditional fuzzy inference systems increases exponentially with the number of input variables, which may cause dimensional catastrophe. To address the limitations of traditional fuzzy inference systems and to combine the advantages of autonomous learning of neural networks, Wu and Er (2000) proposed DFNN. DFNN applies neural networks to fuzzy inference systems so that it can dynamically determine the number of fuzzy rules, and intelligently adjust the system structure according to its predicted error for the new samples. At the same time, the fuzzy theory gives the weights and bias of neural networks practical meaning. DFNN can make full use of the advantages of fuzzy inference systems and neural networks, which is suitable for intelligent evaluation of the states of complex bridge components.

In bridge operation, inspection data including rating scores for the diseases, comprehensive scores for the components, and inspection intervals are accumulated during daily inspection works. DFNN can find the relationships between the scores and the adopted inspection intervals for making inspection decisions when new inspection results are inputted, as shown in Fig. 1.

During the initial inspection, the first inspection to be conducted on a bridge as the bridge becomes part of the bridge inventory, inspectors need to make a detailed assessment of the states of bridge components and make decisions on the interval next inspection needs to be conducted. The index scores of each component and the corresponding comprehensive scores as well as inspection intervals can form a training set, based on which the network can learn and find the weights of each index. After that, the trained network can make decisions on the next inspection intervals according to the scores of the component indexes after an inspection, which avoids

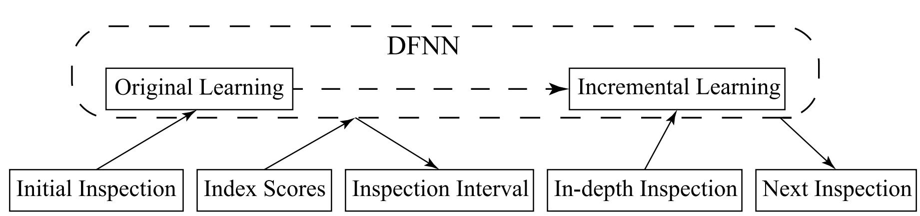


Fig. 1 Decision-making flow for bridge inspection intervals based on inspection process

the experts' investigation needed to determine the weights. With the accumulated deteriorations, the relative importance of different damages may change. To avoid the deviation of the decisions, it is necessary to update the weights in time. In actual bridge inspection works, some in-depth inspections are required when there are difficulties in determining the causes and extents of some damages, which contains more tests and analyses about the state of the structure rather than only visual inspection included in routine inspections. The in-depth inspection results can reflect the changes in the relative importance of damage indexes. Therefore, the network can update its weights incrementally by learning from the in-depth inspection data, thus ensuring the rationality of its decisions.

The structure of DFNN is shown in Fig. 2, which includes the detection index layer, fuzzification layer, activation weight layer, normalization layer, TSK fuzzy rule layer, comprehensive score layer, and inspection interval decision layer. The detection index layer receives the index scores (I), the comprehensive score layer and the inspection interval decision layer give the comprehensive scores (R) and the inspection intervals (I).

The fuzzification layer uses the Gaussian membership function (see Eq. 1) to calculate the affiliation degrees of the indexes.

$$u_{ij}(I_i) = \exp\left[-\frac{(I_i - c_{ij})^2}{\sigma_j^2}\right], i = 1, 2, \cdots, n; j = 1, 2, \cdots, u \tag{1}$$

where u_{ij} is the jth Gaussian membership function for index I_i; c_{ij} is the center of the membership function; σ_j is the width of the function; u is the number of affiliation functions, which is the same as the number of TSK fuzzy rules in the system.

The activation weight layer weights the affiliation degrees to determine the activation degree for each fuzzy rule. The fuzzification layer and the activation weight layer can be replaced by radial basis function (RBF) neurons shown in Eq. 2. The adjustment of the system can be realized by adding or deleting the RBF neurons and adjusting their parameters.

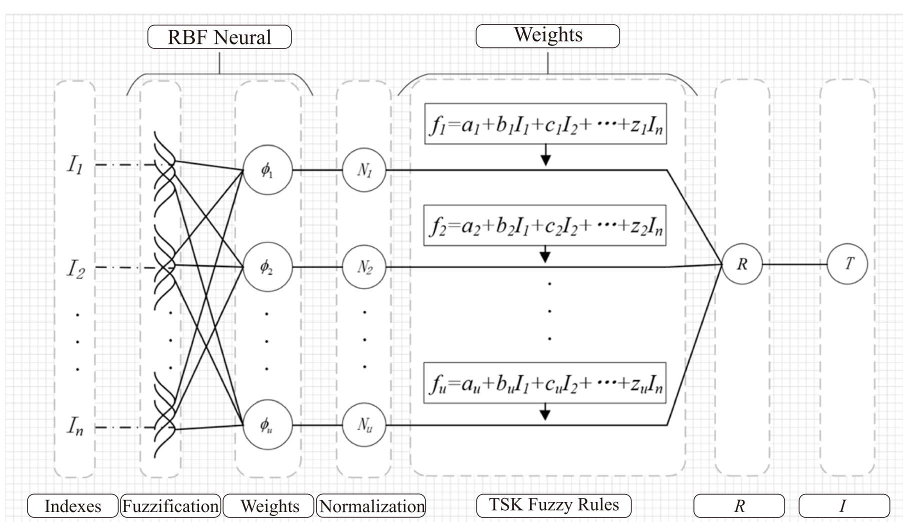


Fig. 2 Architecture of the DFNN combining inspection processes

$$\phi_j = \exp\left[-\frac{\sum_{i=1}^{n}(I_i - c_{ij})^2}{\sigma_j^2}\right], j = 1, 2, \cdots, u \tag{2}$$

The normalization layer normalizes the activation degrees for every fuzzy rule, and the jth normalized value N_j can be expressed as:

$$N_j = \frac{\phi_j}{\sum_{k=1}^{u}\phi_k}, j = 1, 2, \cdots, u \tag{3}$$

Each TSK fuzzy rule in the fuzzy rule layer can be expressed as a weighted linear combination of the detection indexes:

$$f_j = a_j + b_j I_1 + c_j I_2 + ... + z_j I_n, j = 1, 2, \cdots, u \tag{4}$$

where $a_j, b_j, c_j, ..., z_j$ are the parameters in the jth TSK fuzzy rule, which is obtained via the least square method.

2.2 Learning approach for DFNN with a sliding window

The parameters of DFNN, such as c_{ij}, σ_j and u, need to be obtained by autonomous learning. In order to adjust these parameters in time to reflect the changes in the weights of the indexes, the network needs to be updated according to the new in-depth inspection data, that is, the network needs to have incremental learning ability. The traditional learning algorithm adopts the idea of hierarchical learning, that is, the system error limit (k_e) and the admissible boundary (k_d) gradually decrease with the increase of learning times. To achieve hierarchical learning, the training set size needs to be fixed. In the neuron pruning process, the traditional learning algorithm determines the importance of each neuron by calculating the error decline rate (η_i) of each neuron for all training samples, and removes the neurons whose error decline rate is less than a specified threshold (k_{err}). In short, the learning algorithm not only fixes the size of the training set but also regards all the training samples with the same importance in adjusting the network, which hinders the realization of incremental learning.

In order to enable DFNN to learn incrementally, this paper introduces a sliding window and abandons the hierarchical learning in the parameter adjustment and neuron pruning process. That is, k_e and k_d are set as fixed values, and only the samples within a window with a fixed length are considered in calculating the error reduction rate (ERR) (η_i) for each neuron. The learning process for DFNN with a sliding window is shown in Fig. 3.

After new training samples are obtained by in-depth inspections, the sliding window will move forward to eliminate the samples from previous inspections. The introduction of the sliding window enables DFNN to perform incremental learning based on the gradually accumulated data. This feature provides a basis for the system to extract index weights from existing inspection data and to update the weights based on the accumulated data. In addition, the wind driven optimization (WDO) algorithm (Bayraktar 2010) is used to optimize the hyper-parameters of the network in the following analyses.

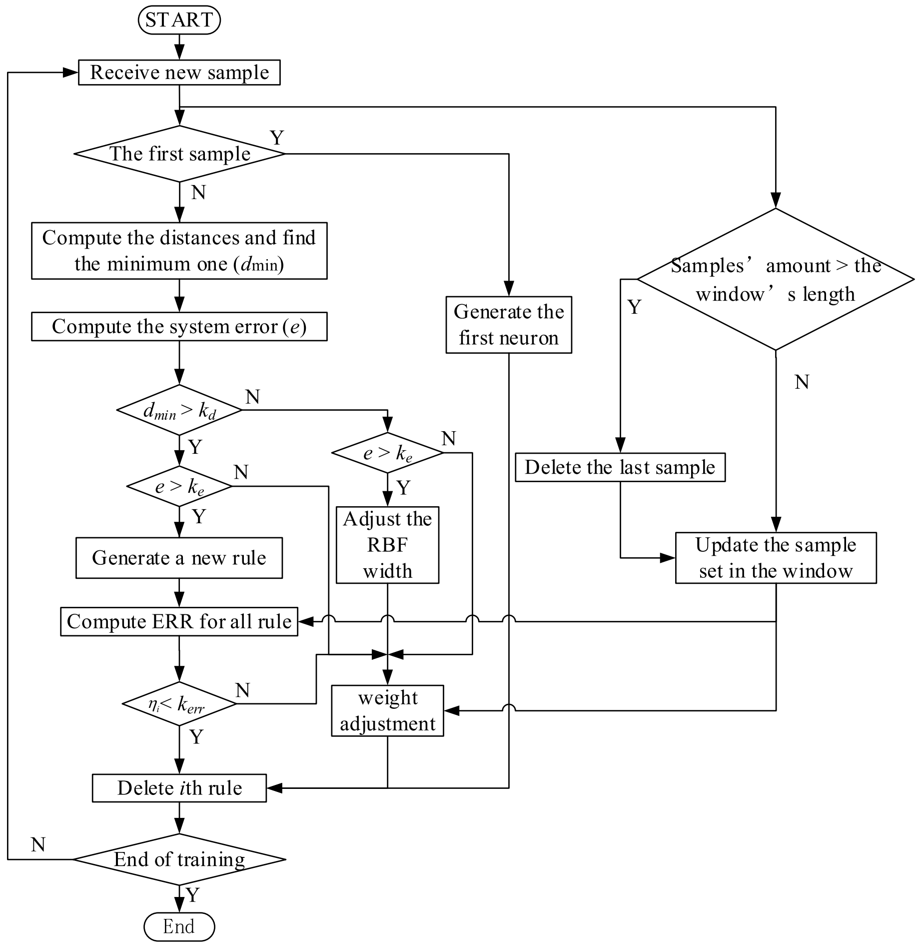


Fig. 3 Learning approach for DFNN with a sliding window

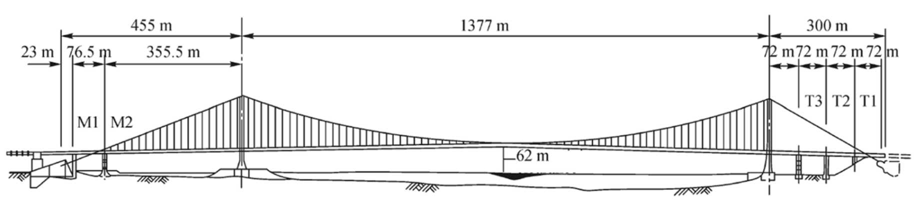


Fig. 4 Configuration of Tsing Ma bridge (Li et al. 2011)

3 Inspection intervals decision for Tsing Ma Bridge

The Tsing Ma Bridge is selected as a protype bridge. The bridge is a suspension bridge with a main span of 1377m. To monitor its state, about 350 sensors were installed. These monitoring equipment, communication equipment and data center constitute a SHM system and provide a large amount of measured data for the bridge operation and inspection. The main span arrangement of the bridge is shown in Fig. 4.

Based on AHP, Li et al. (2011) established a bridge evaluation system that integrates monitoring data and visual inspection results. Its architecture is shown in Fig. 5, in which C_1 is the damage state index, which refers to the degree of the damage that is

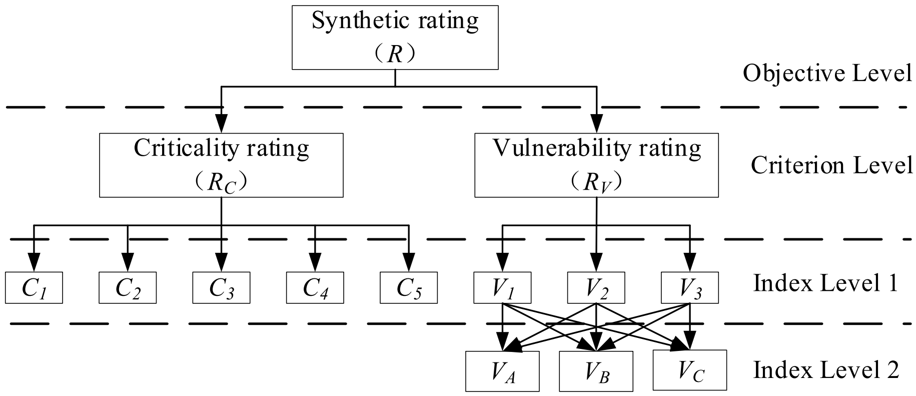


Fig. 5 Index system for components rating (Li et al. 2011)

Table 1 Inspection intervals for different comprehensive scores (Li et al. 2011)

Degree	Comprehensive score (*R*)	Inspection interval (*I*/year)
I	[75,100]	0.5
II	[57.5,75)	1
III	[25,57.5)	2
IV	[0,25)	6

known but not serious enough to need immediate repair or cannot be repaired due to technical reasons. C_2 is the strength utilization coefficient, that is, the ratio of the load effect on the component to its capacity. C_3 is the residual fatigue life of the component. C_4 is the substitutability of the force transmission path, which represents the possibility that the load borne by the component is shared by other components when the component is damaged. C_5 is the bearing capacity of the component under extreme conditions. V_1 represents very slow damage, such as concrete carbonation, steel corrosion, etc. V_2 represents very rapid damage, such as vehicle and ship impact. V_3 represents relatively slow damage, such as deformation caused by temperature changes. V_A, V_B and V_C represent the exposure degree of the component, the possibility of the component's damage being found in inspection, and the influence of the component damage on structural integrity, respectively. The vulnerability index is calculated by its sub-index, as shown in Eq. 5.

$$V_i = \sqrt[3]{V_{iA} \times V_{iB} \times V_{iC}} \tag{5}$$

Combined with the actual component conditions and inspection intervals of the Tsing Ma Bridge, Li et al. (2011) established the relationship between the component comprehensive score and the inspection interval, as shown in Table 1.

Considering that the increasement in the number of neurons will complicate the network and the conversion between the vulnerability index and its subindexes does not involve the weights to be adjusted, only the importance index and vulnerability index (index layer 1 in Fig. 5) are considered as the inputs to the network. Based on the literature (Li et al. 2011) to simulate the evaluation process, the comprehensive rating scores and corresponding inspection intervals for different components were generated and used as training samples for the network. The weights of each index for the simulation are shown in Table 2.

3.1 DFNN parameters and inspection intervals decision

In the initialization phase, the width of the first RBF neuron is set as $w_0 = 25$; the overlap coefficient, between the new neuron and existing neurons, is set as $k = 2.2$; the RBF neuron width amplification coefficient is set as $k_w = 2.2$; the system error limitation is set as $k_e = 0.1$; the system admissible boundary is set as $k_d = 20$; and the neuron pruning threshold is set as $k_{err} = 0.05$. The network hyper-parameters optimized by WDO are: $w_0 = 19.37$, $k = 2.94$, $k_w = 2.49$, $k_e = 0.11$, $k_d = 28.78$, $k_{err} = 0.06$. The network is trained using the initial and optimized hyper-parameters, respectively, and the sliding window length is set to 100. To determine the number of samples contained in the training set and the test set, several training processes are conducted, and the numbers that can show the differences between the system with the initial parameters and that with the optimized parameters (see Figs. 6 and 7), 200 samples for the training set and 100 samples for the test set, are adopted in the following analyses.

The number of TSK fuzzy rules (f_i in Fig. 2), which is the same as the number of RBF neurons, in the training process and the prediction error are shown in Fig. 6, and the test results are shown in Fig. 7. The prediction error refers to the absolute distance between the decision value from the network and the target value of the next sample that belongs to the training set but has not been inputted into the network, and the test result refers to the relative error between the decision value and the target value for the test samples. From Fig. 6, it can be found that the number of the fuzzy rules in the network with the initial parameters rises continuously with the accumulating training samples. On the contrary, the number of the fuzzy rules is stable after 25 training samples are inputted when the optimized parameters are adopted. The prediction error of the network using the optimized parameters is smaller than that of the network using the initial parameters, and the relative error of the former is also smaller. The both indicate that the optimized parameters can

Table 2 Index weights for the bridge rating system (Li et al. 2011) (Group 1)

Rating	Weight
Criticality rating (R_C)	0.5
C_1	0.1237
C_2	0.3945
C_3	0.2343
C_4	0.1238
C_5	0.1237
Vulnerability rating(R_V)	0.5
V_1	0.5
V_2	0.25
V_3	0.25

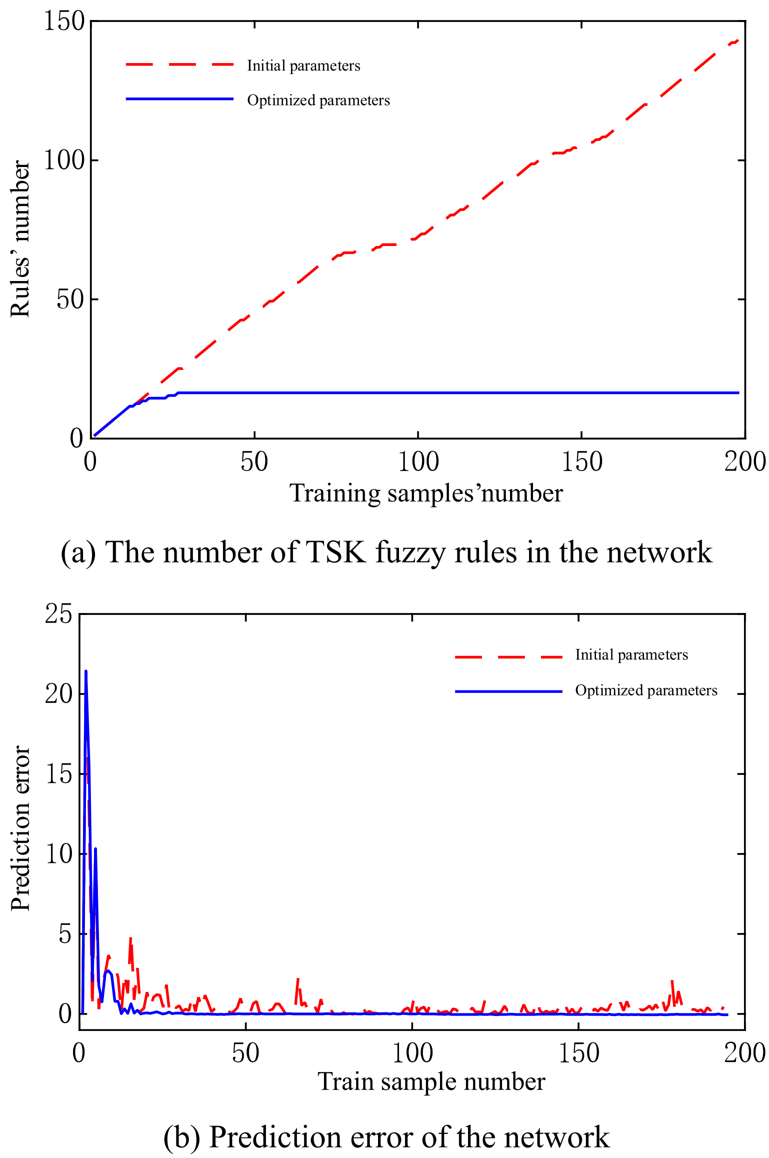
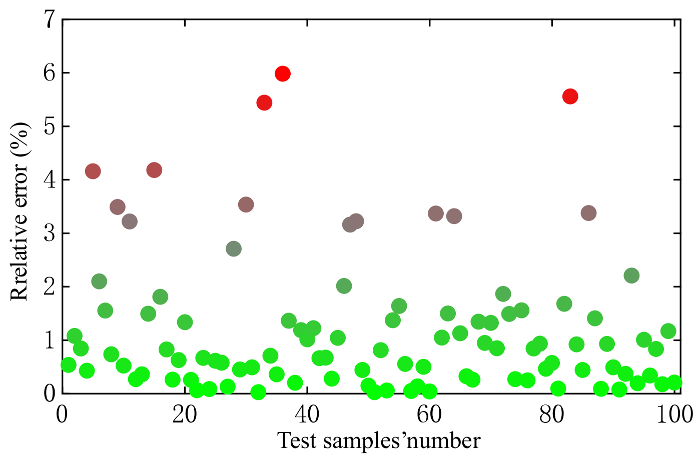


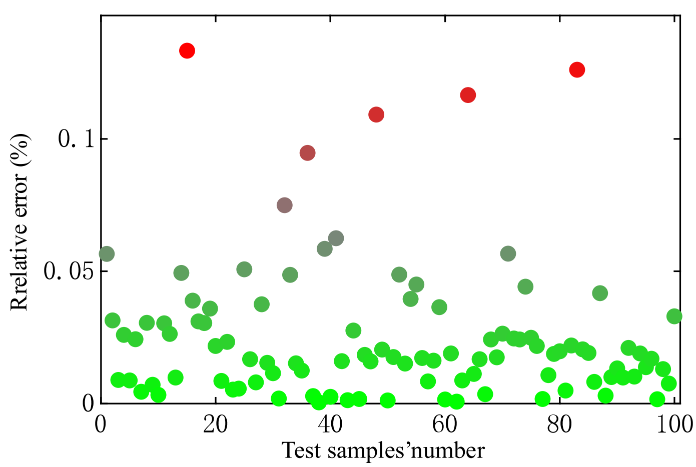
Fig. 6 Training process monitoring before and after the hyperparameters' optimization

effectively improve the learning efficiency and performance of the network so that they will be adopted in the following analyses.

Table 3 compares the comprehensive scores (R) and the inspection intervals (I) of some components of the Tsing Ma Bridge obtained from the network and the literature (Li et al. 2011). The comparison results show that for the components with the same index scores, the comprehensive scores from the two methods are slightly different. However, since the inspection interval decision bases on the section the comprehensive score locates in, there is a tolerance for the scores, so the decision results are the same. Therefore, the network can extract the weights from the existing inspection data and make accurate decisions on the inspection intervals.



(a) Relative error from the network using the initial parameters



(b) Relative error from the network using the optimized parameters

Fig. 7 Test results before and after the hyper-parameters' optimization

3.2 Incremental learning of the network

After the network learns the initial inspection data, it needs to be updated according to the gradually accumulated inspection data. This section simulates the accumulated inspection data through changing the weights in the AHP method. The weights for the first 100 training samples are shown in Table 2, and the weights for the last 100 training samples and 100 test samples are shown in Table 4. The sliding window length is set to 50.

The number of fuzzy rules, the prediction error and the root mean square of the prediction errors for the samples within the window during the training process are shown in Fig. 8 (the root mean square error during the windowless training process refers to the root mean square error of all the training samples), and the test results are shown in Fig. 9.

Before the training samples based on the new weights (see Table 4) appear, the trend of each monitored variable in the training processes with and without the

Table 3 Comprehensive scores (*R*) and inspection intervals (*I*/year) for some components

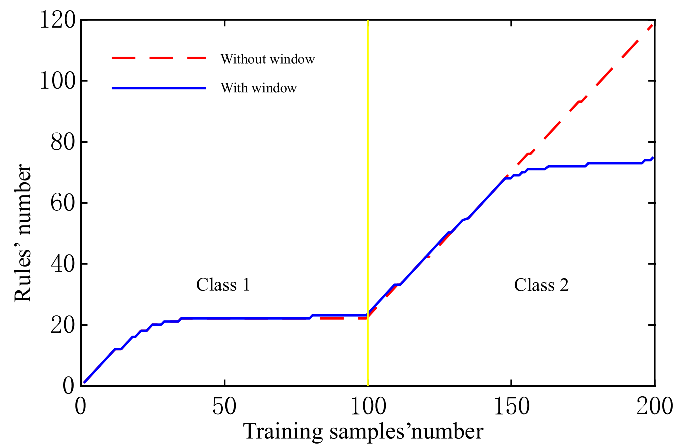
Element	Component	C_1	C_2	C_3	C_4	C_5	V_1	V_1	V_3	Li et al. (2011)		DFNN	
										R	***I***	***R***	***I***
Suspension cables	Main cables	0	100	0	100	100	100	100	0	69.59	2	69.63	2
	Strand shoes	0	67	0	67	100	79.4	79.4	0	53.32	2	53.33	2
	Shoe anchor rods	0	67	0	67	100	79.4	79.4	0	53.32	2	53.33	2
	Anchor bolts	0	67	0	67	100	79.4	79.4	0	53.32	2	53.33	2
	Cable clamps and bands	0	67	0	67	33	100	63	0	52.28	2	52.28	2
Suspenders	Hangers	0	100	67	67	33	79.4	79.4	0	63.53	2	63.53	2
	Hanger connections: stiffeners	0	100	0	67	33	79.4	79.4	0	55.69	1	55.69	1
	Hanger connections: bearing plates	0	100	0	67	33	79.4	79.4	0	55.69	1	55.69	1
Towers	Legs	0	67	0	100	67	100	0	0	48.54	2	48.54	2
	Portals	0	67	0	100	67	100	0	0	48.54	2	48.54	2
	Saddles	0	67	0	100	67	100	0	0	48.54	2	48.54	2
Anchorages	Chambers	0	0	0	100	100	100	0	0	37.37	2	37.35	2
	Prestressed anchors	0	100	0	67	67	79.4	0	0	47.86	2	47.86	2
	Saddles	0	67	0	100	67	79.4	0	0	43.39	2	43.39	2
Piers	Legs	0	0	0	100	100	100	0	0	37.37	2	37.35	2
	Cross-beams	0	67	0	100	67	100	0	0	48.54	2	48.54	2

Table 4 Varied weights for the bridge rating system based on AHP (Group 2)

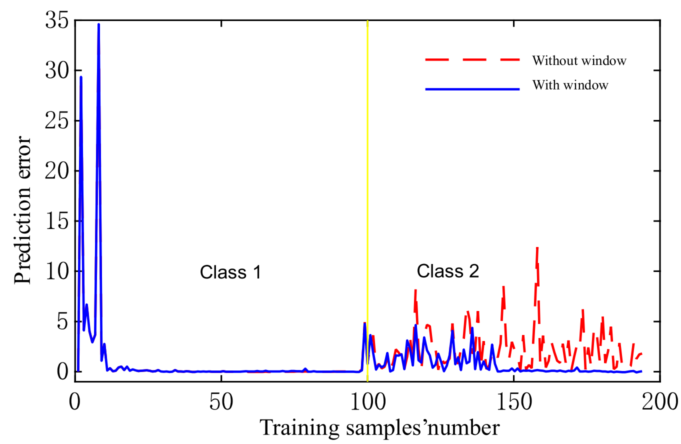
Rating	Weight
Criticality rating (R_C)	0.5
C_1	0.0985
C_2	0.4304
C_3	0.2741
C_4	0.0985
C_5	0.0985
Vulnerability rating (R_V)	0.5
V_1	0.6
V_2	0.2
V_3	0.2

sliding window is basically the same. After that, all of the monitored variables begin to be adjusted, and the number of fuzzy rules and the prediction error increase at the same time. However, in the process of windowless training, because of the influence of the training samples based on the original weights (see Table 2), the prediction error for the new sample and the root mean square error for the trained samples will not decrease with the accumulation of new samples. In the process of windowed training, when all the samples in the window are updated, the network can eliminate the influence of the samples based on the original weights in time. The number of fuzzy rules will be stable and the prediction error as well as the root mean square error will fall back to near zero. The test results of the network using the windowed learning method are also significantly better than that using the windowless learning method.

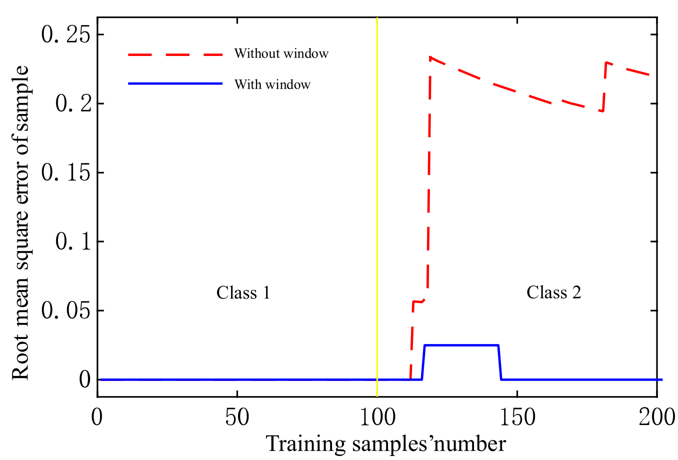
When the sliding window length is changed, the network's training process and the average relative error for the test samples are shown in Figs. 10 and 11. The average relative error reflects the error between the decisions and the targets of the test samples (test sample number is 100). It can be seen from the graphs that when the sliding window is too short (less than 50), the number of fuzzy rules continues to grow, and the prediction errors for new samples fluctuate significantly, but the root mean square error for the samples in the window fluctuates small. The reasons can be summarized as: when the length of the sliding window is too short, the samples in the window is too little to provide sufficient knowledge, so that the network can only make accurate predictions for the learned samples. When the length of the sliding window is suitable (between 50 and 100), the number of fuzzy rules, the prediction error, and the root mean square error tend to be stable after all the samples in the window are updated, which indicates that the network has been update. During this stage, the average relative error of the test samples closes to zero and the increase of the sliding window length has no obvious effect on the test results. While the sliding window length is too large, due to the lack of samples based on the new weights, the network adjustment still needs to consider the two sample groups at the same time, so the average relative error for the test samples based on the new weights is large. At this time, more training samples based on new weights are needed to update the network.



(a) The number of fuzzy rules in the network with and without the sliding window

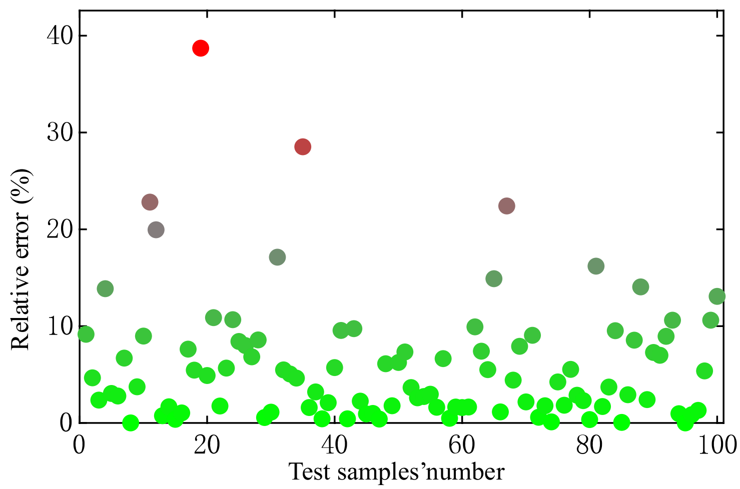


(b) Prediction error of the networks with and without the sliding window

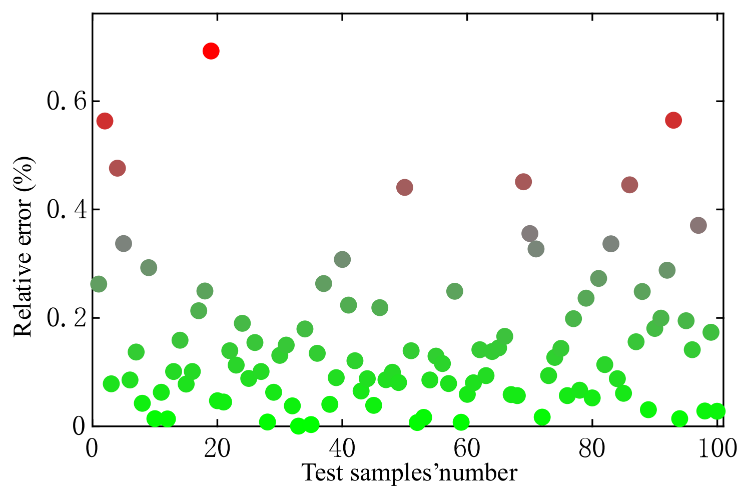


(c) Root mean square of the prediction errors with and without the sliding window

Fig. 8 Training process monitoring of the network with and without the sliding window



(a) Relative error from the network without the sliding window



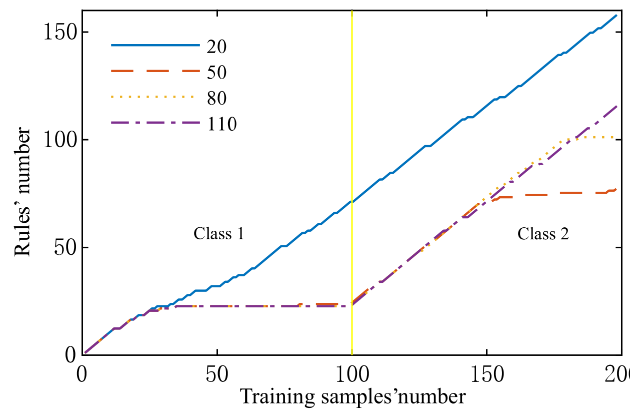
(b) Relative error from the network with the sliding window

Fig. 9 Test results of the network with and without the sliding window

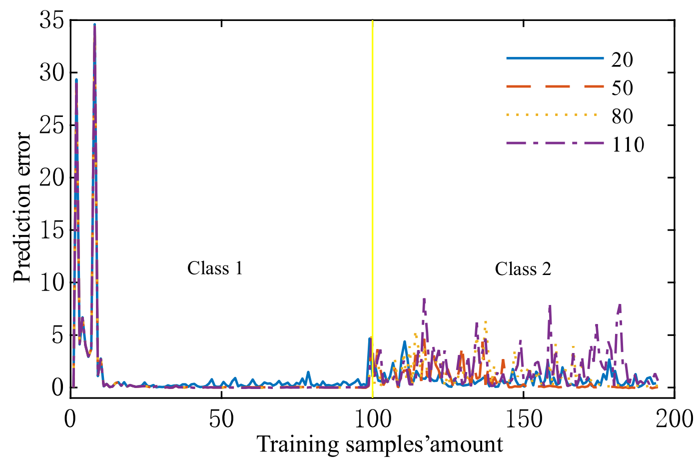
4 Conclusions

In this paper, a bridge inspection interval decision-making system is established based on DFNN, and a sliding window is introduced to enable the system to learn incrementally. The main conclusions are listed as follows:

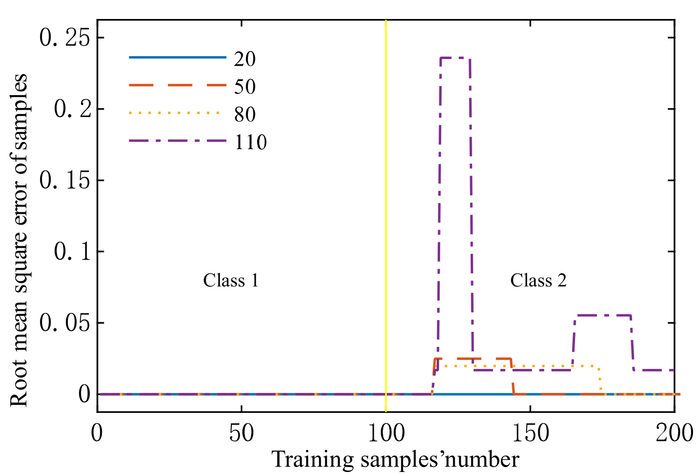
1 DFNN can extract the weights of the indexes from the existing inspection data, and then evaluate the condition of bridge components and make inspection interval decisions according to the scores of the indexes.
2 The introduction of the sliding window enables the DFNN to learn incrementally. When the samples with different weights are provided, the test error of the network using the windowless learning algorithm ups to 38%, while that of the network using the windowed learning algorithm is only 0.72%.



(a) The number of TSK fuzzy rules in the network with various window lengths



(b) Prediction error with various window lengths



(c) Root mean square error with various window lengths

Fig. 10 Training processes with various lengths of the sliding window

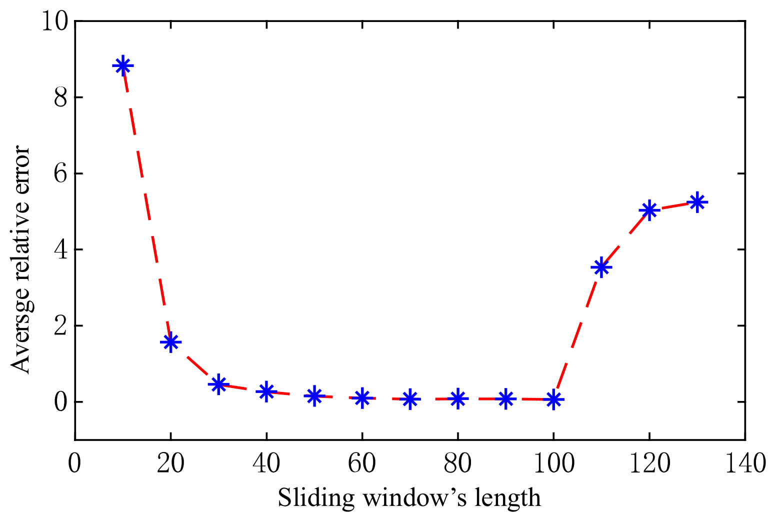


Fig. 11 Test result with various lengths of the sliding window

3 When the length of the sliding window is too small, the samples in the window are not representative enough so that the performance of the network is poor. At this time, increasing the length of the sliding window can effectively improve the network's performance. However, the longer sliding window length means that more training samples are needed, and the effect of increasing the sliding window length on the network's performance is gradually weakened. In the inspection interval decision for the Tsing Ma Bridge, the ideal sliding window length is 50.

Authors' contributions
Guo-Qing Zhang: Conceptualization, Formal analysis, Data calculation, Investigation, Software, Validation, Visualization, Writing-original draft. Quan Min: Data calculation, Investigation, Writing-review & editing. Bin Wang: Conceptualization, Resources, Project administration, Methodology, Supervision, Writing-review & editing.

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Declarations

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