ABSTRACT: This presentation summarizes the development of vibration-based structural health monitoring and damage detection methods and their applications to cable-supported bridges. It has been shown that because of very low modal sensitivity of the structures with respect to damage at a component level, only the methods which have high tolerance to incompleteness of measured data, measurement noise, modeling error and structural uncertainty are applicable to large-scale cable-supported bridges for vibration-based damage identification. The research focus has been given to eliminate the environmental effects in vibration-based damage detection. Both parametric and non-parametric procedures are proposed for eliminating the temperature effect in vibration-based damage detection, and several illustrative examples are provided.

KEY WORDS: Cable-supported bridge; Structural health monitoring; Vibration-based damage detection.

1 INTRODUCTION

Maintaining the safe and reliable operation of vital infrastructure systems that society depends upon is critical to securing the well-being of people, protecting significant capital investments, and supporting the vitality of the global economy. However, infrastructure systems cannot last forever; even after construction, these complex systems begin to deteriorate within the demanding operational environment in which they are placed. Given the costs associated with infrastructure repair and the high environmental impact of infrastructure construction, government authorities worldwide are increasingly seeking sensing and instrumentation systems to more objectively monitor their crucial infrastructure systems to ensure structural and operational safety. Structural health monitoring (SHM) technology can provide engineers and owners with early warnings on damage and structural deterioration prior to the need for costly repairs or situations that can lead to catastrophic structural collapses. The past two decades have witnessed a rapid increase in the applications of SHM technology to various civil engineering structures around the world [1-6].

The development of SHM technology in Hong Kong has evolved for over fifteen years since the implementation of the so-called “Wind And Structural Health Monitoring System (WASHMS)” on the suspension Tsing Ma Bridge in 1997. Five long-span cable-supported bridges in Hong Kong, namely the Tsing Ma (suspension) Bridge, the Kap Shui Mun (cable-stayed) Bridge, the Ting Kau (cable-stayed) Bridge, the Western Corridor (cable-stayed) Bridge, and the Stonecutters (cable-stayed) Bridge, have been instrumented by the Highways Department of the Hong Kong SAR Government with sophisticated long-term SHM systems [7-9]. The SHM systems also were periodically updated in order to effectively execute the functions of structural condition monitoring and structural degradation evaluation under in-service condition. A lot of investigations on using the monitoring data from the instrumented bridges for structural health and condition assessment have been carried out [10-18]. This paper outlines the development of structural health monitoring and damage detection methods for cable-supported bridges based on long-term vibration monitoring data.

2 BRIDGE SHM SYSTEMS IN HONG KONG

The SHM systems for the five cable-supported bridges in Hong Kong were designed and implemented for real-time monitoring of four categories of parameters: (i) environments (wind, temperature, seismic, humidity, corrosion status, etc.), (ii) operational loads (highway traffic, railway traffic), (iii) bridge features (including static features such as influence coefficients and dynamic features such as modal parameters), and (iv) bridge responses (geometrical profile, cable force, displacement/deflection, strain/stress histories, cumulative fatigue damage, etc.). Figures 1 to 5 show the SHM systems deployed on the bridges. In accordance with a modular design concept [19], each system is composed of six modules, i.e., Module 1: Sensory System (SS), Module 2: Data Acquisition & Transmission System (DATS), Module 3: Data Processing & Control System (DPCS), Module 4: Data Management System (DMS), Module 5: Structural Health Evaluation System (SHES), and Module 6: Inspection & Maintenance System (IMS). The SS and DATS are sensors, on-structure data acquisition units (DAUs), and cabling networks for signal collection, processing and transmission. The DPCS is a computer system for the execution of system control, system operation display, and processing and analysis of data. The DMS refers to a database or data warehouse system for the storage and retrieval of monitoring data and analysis results. The SHES, which is the core of the SHM system, is a high-performance computer system equipped with appropriate software and advanced analysis tools for the execution of finite element analysis, sensitivity analysis and model updating, bridge feature and response analysis, diagnostic and prognostic analysis, and visualization of analyzed results. It includes an on-line structural condition evaluation system and...
Figure 1. SHM system for Tsing Ma Bridge (TMB).

Figure 2. SHM system for Kap Shui Mun Bridge (KSMB).

Figure 3. SHM system for Ting Kau Bridge (TKB).

Figure 4. SHM system for Western Corridor Bridge (WCB).

Figure 5. SHM system for Stonecutters Bridge (SCB).

an off-line structural health and safety assessment system. The IMS is a laptop-computer-aided portable system for the inspection and maintenance of the SHM system itself.

The SHM systems were devised for the objectives: (i) to have a better understanding of the structural behavior of the cable-supported bridges under their in-service condition; (ii) to develop and validate the bridge evaluation techniques based on measurement results; (iii) to setup/calibrate/update the monitoring and evaluation models and criteria for describing and limiting the variation ranges of the physical parameters that influence bridge performance under in-service condition; (iv) to evaluate structural integrity immediately after rare events such as typhoons, strong earthquakes and vessel collisions, etc.; (v) to provide information and analytical tools for the planning, scheduling, evaluating and designing of effective bridge inspection and maintenance strategies; and (vi) to minimize the lane-closure time required for exercising bridge inspection/maintenance activities, hence maximizing the traffic operational period of the bridges. The deployed SHM systems have operated continuously and steadily more than ten years.

3 VIBRATION-BASED DAMAGE ALARMING

The implementation of the SHM systems highlights the necessity of developing practical damage detection methods for large-scale civil structures. Among varieties of damage detection methods available, the vibration-based diagnosis methods, which use the measured changes in the dynamic features of a structure to indicate structural damage or degradation, have been extensively investigated. Most of these algorithms neglect the effects of environmental changes on the dynamic characteristics of the underlying structure. In reality, however, civil structures are subject to varying environmental and operational conditions such as temperature, wind, traffic, humidity, and solar radiation. These environmental effects also cause changes in dynamic and modal properties, which may mask the changes caused by structural damage. If the effects of environmental conditions are not taken into account in damage detection, false-positive or false-negative diagnosis may occur. Environmental effects have been identified as one main pitfall that limits the successful applications of vibration-based damage detection methods to large-scale civil structures. Modeling of the correlation between modal parameters and environmental effects with the use of long-term monitoring data obtained from the instrumented bridges in Hong Kong has been studied by employing various statistical learning algorithms [20-23].

Alarming the presence of structural damage at the earliest possible stage is the most primary objective of structural damage detection. The philosophy of the vibration-based structural damage alarming is rather simple: during the normal operation of a structure, damage-sensitive features (dynamic characteristics) that characterize the healthy state of the structure are first extracted. Making use of some novelty detection technique, subsequent data from an unknown state of the structure are examined to see if the features deviate from the healthy state. Ideally, an alarm will be signaled if the features shift from the healthy state. However, false-positive or false-negative damage may be alarmed in the presence of the environmental effects.
3.1 Non-parametric Approach

Several non-parametric methods to eliminate the environmental effects in structural damage alarming have been proposed [24-28]. The principle behind them is that the causation pattern between the environmental conditions and damage-sensitive features is inherent in the structural response. The pattern can be extracted from the measurement data of a structure in a healthy state even when the environmental conditions are not measured; and then it can be utilized to examine data from an unknown state of the structure to see if the data are generated from this pattern. One of the non-parametric methods is the auto-associative neural network (AANN) technique, which is the neural network realization (Figure 6) of the nonlinear principal component analysis for feature extraction and novelty detection of multivariate data [29]. The advantages of this technique are that it doesn’t require a structural model and accommodates uncertainty. Two capabilities are expected when applying the AANN-based damage alarming technique to real structures. The first capability is to avoid false-positive alarm; that is, alarm shall not be signaled if the environmental conditions, at which the damage-sensitive features are measured, change but no damage really occurs. The second capability is to avoid false-negative alarm; that is, the AANN shall be able to detect damage independent of the environmental conditions at which the identification of damage-sensitive features is performed. In practice, the above capabilities are closely related to two important issues, i.e., the environment-tolerant capacity of the AANN and the setup of the alarming threshold.

![Figure 6. Auto-associative neural network (AANN).](image)

The environment-tolerant capacity of an AANN is related to its generalization capability. Efforts have been made to seek a generalization technique to enhance the environment-tolerant capacity in structural damage alarming [15]. Three AANN models with the use of the AIC and FPE technique, early stopping technique, and Bayesian regularization technique, respectively, are formulated using the finite element model (for the simulation of different damage scenarios) and the measured modal frequencies (Figure 7) of the cable-stayed Ting Kau Bridge, and are compared with the baseline AANN model which is trained by the conventional training algorithm. They are referred to as NN1, NN2, NN3, and NN0, respectively. Their environment-tolerant capacity is evaluated as per the compromise between the capabilities to avoid false-positive alarm and to avoid false-negative alarm.

The capability of NN0, NN1, NN2, and NN3 to avoid false-positive alarm is examined using a set of unseen testing data, which are also obtained from the intact (healthy) bridge but measured under different environmental conditions. By feeding the unseen testing data into the four AANN models, their outputs are obtained and used to construct the novelty indices in the testing phase. Figures 8 and 9 show the novelty index sequences in the testing phase (dotted line) compared with the novelty index sequences in the training phase (solid line) obtained from NN0 (formulated by the conventional training technique) and NN3 (formulated by the Bayesian regularization technique), respectively. There is an obvious deviation in the novelty index between the training and testing phases for NN0, while no significant deviation is observed in the novelty index between the two phases for NN3. Because the test data are also acquired from the healthy structure (but under different environmental conditions), it is expected that the AANN would not generate deviation in the novelty index in statistical sense between the training and testing phases.

An alarming threshold of the novelty index based on the confidence interval and probability distribution of the novelty

![Figure 7. Measured modal frequencies for first 8 modes.](image)

![Figure 8. Novelty index of healthy structure for NN0.](image)

![Figure 9. Novelty index of healthy structure for NN3.](image)
The capability of the AANN models to avoid false-negative alarm is then examined. Because NN0 and NN1 failed to eliminate false-positive alarm, only NN2 and NN3 are considered here to see if they are capable of avoiding false-negative alarm. The ‘measured’ modal frequencies in various damage scenarios are generated by superposing the computed modal frequencies from a validated finite element model (FEM) of the bridge with the environmental effects that were extracted from the real monitoring data. Figures 10 and 11 show the novelty index sequences in the testing phase compared with the novelty index sequences in the training phase obtained from NN2 and NN3, respectively, where the damage is introduced by losing torsional and bending stiffness of a bearing element at the main tower. The damage-induced change of modal frequencies for the first eight modes which were used to formulate the AANN models is $8.710 \times 10^3$ Hz ($\approx 5.240\%$) at maximum. Table 2 provides the statistics of the novelty index outliers in the testing phase. In this case, $r_0$ values obtained from NN2 and NN3 are greatly higher than the prescribed probability of type I error (63.077% vs 2.000% and 58.462% vs 2.000%). Both NN2 and NN3 clearly signal the damage, and therefore the capability of NN2 and NN3 to avoid false-negative alarm is validated. After comparison in different damage scenarios, it has been shown that the early stopping technique is most suitable for enhancing the environment-tolerant capacity of the AANN as it achieves the best compromise between the capabilities to avoid false-positive alarm and to avoid false-negative alarm.

![Figure 10](image1.png)

**Figure 10. Novelty index of damaged structure for NN2.**

![Figure 11](image2.png)

**Figure 11. Novelty index of damaged structure for NN3.**

<table>
<thead>
<tr>
<th>AANN</th>
<th>$N_0$ (%)</th>
<th>$r_0$ (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>NN0</td>
<td>10</td>
<td>4.049</td>
</tr>
<tr>
<td>NN1</td>
<td>53</td>
<td>11.648</td>
</tr>
<tr>
<td>NN2</td>
<td>2</td>
<td>0.810</td>
</tr>
<tr>
<td>NN3</td>
<td>1</td>
<td>0.405</td>
</tr>
</tbody>
</table>

Table 1. Outliers of novelty index for healthy structure.

<table>
<thead>
<tr>
<th>AANN</th>
<th>$N_0$ (%)</th>
<th>$r_0$ (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>NN2</td>
<td>287</td>
<td>63.077</td>
</tr>
<tr>
<td>NN3</td>
<td>266</td>
<td>58.462</td>
</tr>
</tbody>
</table>

Table 2. Outliers of novelty index for damaged structure.

### 3.2 Parametric Approach

The SHM systems for the five cable-supported bridges in Hong Kong provide simultaneous measurement of dynamic responses and temperature at different structural positions. When both dynamic properties and temperature are measured,
a parametric method can be applied to eliminate the temperature effect in vibration-based structural damage detection. In this method, a correlation model between the modal frequencies and temperatures is first formulated by a statistical learning algorithm, such as the back-propagation neural network (BPNN) technique, with the use of long-term monitoring data of modal frequencies and temperatures from the healthy structure. The configuration and parameters of the BPNN model are optimized in effort to achieve good generalization (prediction) performance. With the formulated correlation model, the modal frequencies measured under different temperature conditions can be normalized to an identical reference status of temperature so as to eliminate the temperature effect. To this end, an arbitrary reference status of temperature is set. The reference temperature together with the temperatures at which the modal frequencies were measured, is passed to the correlation model to produce a reference frequency $f_i^R$ and the predicted frequencies $f_i^P$. Thus the temperature-caused change in the modal frequencies is obtained by subtracting the reference frequency from the predicted frequencies. Then the normalized modal features $f_i^N$ are obtained by subtracting the temperature-caused frequency change from the measured frequencies [14]

$$f_i^N = f_i^M - \Delta f^T = f_i^M - \left(f_i^R - f_i^B\right)$$

where $i$ represents the sample order in the sequence of the measured modal frequencies. After eliminating the temperature effect on the modal frequencies, damage is assumed to be the source responsible for the variation in modal frequencies. Then, structural damage alarming can be conducted by the aforementioned AANN technique with the use of the normalized modal frequencies.

The capability of the parametric method in eschewing false-positive alarm is examined using a set of unseen monitoring data obtained from the intact (healthy) bridge but measured under different environmental conditions. For comparison, two AANN models have been formulated: one (referred to as AANN-1) uses the normalized modal frequencies, and the other one (referred to as AANN-0) uses the originally measured modal frequencies. AANN-0 (trained with the originally measured modal frequencies) is first examined with the unseen testing data that were obtained from the same structure in healthy status. Figure 12 shows the novelty index sequence in the testing phase (dotted line) in comparison with the novelty index sequence in the training phase (solid line). As there is an obvious shift in the novelty index sequences between the testing and training phases (the quantitative evaluation is the same as before), AANN-0 issues an alarm on damage. It is contradictory to the fact that the testing data are also obtained from the healthy structure though measured at different environmental conditions. Therefore, the alarm is false-positive.

AANN-1 (trained with the normalized modal frequencies) is then examined with the same unseen testing data that were obtained from the structure in healthy status. Figure 13 shows the novelty index sequences in the testing phase (dotted line) and in the training phase (solid line) produced by AANN-1. As one might expect, no observable deviation appears in the novelty index sequences between the testing and training phases. Therefore, the parametric method is shown to be able to eliminate the temperature effect and eschew false-positive damage alarm.

The performance of the parametric method in detecting the presence of structural damage with use of monitoring data obtained under different environmental conditions is further examined. Again, the ‘measured’ modal frequencies in various damage scenarios are generated by superposing the computed modal frequencies from a validated FEM of the bridge with the environmental effects that are obtained from the real monitoring data. Figure 14 shows the novelty index sequences in the testing phase compared with the novelty index sequences in the training phase obtained from AANN-1, where the damage is introduced by losing torsional and bending stiffness of a bearing element at the main tower (same as the damage case before). The difference in the means of novelty indices between the testing and training phases for
this damage case has increased by 105.16% in comparison with the intact structure. Hence, the capability of AANN-1 to avoid false-negative alarm is validated.

4 VIBRATION-BASED DAMAGE LOCALIZATION

4.1 Multi-novelty indices for identifying damage region

The AANN-based damage alarming technique can be extended to roughly diagnose the damage region without need of structural model. Multi-novelty indices are formulated for this purpose. In this approach, the structure is partitioned into a number of regions and it is assumed that there are vibration transducers at each region. For each structural region, a neural network based novelty detector is formulated by using the global natural frequencies and the local modal components measured from the sensors located within this region. The damage region is signaled by the corresponding novelty index if it exhibits a deviation from the training phase to the testing phase.

For illustration, a simulation study is made by dividing the main span deck of the suspension Tsing Ma Bridge into five regions equally in the longitudinal direction. It is assumed for each region five modal components are ‘measured’. Then the modal flexibility values [30] at the five nodes for each region are computed from a 3D FEM of the bridge by taking the first five modes. The analytically evaluated modal flexibility values are corrupted with a normally distributed random noise with a variance of 0.005 to generate the ‘measured’ modal flexibility sequences. Five AANN models, one for each region, are formulated for damage region identification. Each AANN is trained using the five modal flexibility sequences obtained for the corresponding region. Figure 15 shows the novelty detection results by using the multi-novelty indices, for the damage case in which the damage is introduced by removing two opposite longitudinal bottom chords at the mid-span deck section. For the structural regions I, II, IV and V, no damage is signaled because the novelty index sequences in the training phase do not deviate from those in the testing phase. For the structural region III, the novelty index sequence in the training phase significantly deviates from that in the testing phase, indicating damage occurrence in this region. Indeed, the true damage occurs at the mid-span deck within the region III.

4.2 Probabilistic neural network for damage localization

The probabilistic neural network (PNN) [31, 32] performs the Bayesian decision analysis with the Parzen windows estimator cast into an artificial neural network framework. When applied to damage identification, the PNN uses exemplars from the undamaged and damaged system to establish whether a new measurement of unknown origin comes from the undamaged class or the damaged class. Since the PNN directly casts the probability density functions (PDFs) of training samples in the network, the network configuration is convenient for dealing with the noisy and series measurement data when applied for damage identification. A salient feature of the PNN is that it can explicitly accommodate the noise characteristic as neuro-weights in the trained network.

Figure 16 shows a three-layer probabilistic neural network to be used for damage localization in the present study. It consists of input (distribution) layer, pattern layer and

Figure 15. Multi-novelty indices based on modal flexibility.
summation layer. An input vector \( \mathbf{X} = \{x_1, x_2, \ldots, x_p\}^T \) to be classified is applied to the neurons of the distribution layer that just supply the same input values to all the pattern units. In our study, this input vector consists of \( p \) modal parameters (natural frequencies, mode shapes or their combination). For the purpose of damage localization, the so-called combined modal parameters [32] which are only dependent on damage location but independent of damage extent are a good choice for the input parameters. In the pattern layer, there are \( s \) pattern classes, each representing a possible damage location. The number of pattern classes depends on a specific structure. Each neuron in the pattern layer forms a dot product of the input vector \( \mathbf{X} \) with a weight vector \( \mathbf{W}_j \) of a given class, \( z_j = \mathbf{X}^\top \mathbf{W}_j \), and then performs a nonlinear operation on \( z_j \) before output to the summation layer. The activation function used here is \( g(z_j) = \exp(z_j)/\sigma^2 \) where \( \sigma \) is a smoothing parameter. In the summation layer, each neuron receives all pattern layer outputs associated with a given class. For instance, the output of the summation layer neuron corresponding to the class \( k \) is

\[
f_k(\mathbf{X}) = \sum_{j=1}^{n_k} z_{kj} = \sum_{j=1}^{n_k} \exp(\mathbf{X}^\top \mathbf{W}_{kj} - 1)/\sigma^2 \tag{2}
\]

With Equation (2), the kernel density estimators for PDFs have been cast into the PNN by setting the network weight vectors as the corresponding training vectors. Such configured PNN outputs in the summation layer the PDF estimates for each pattern class at the test vector point. The pattern class with the largest PDF implies the class of the current test vector point, and the damaged deck segment is identified by the pattern class with the largest PDF.

For illustration, a simulation study of damage localization using the PNN is made on the Tsing Ma Bridge deck. The bridge main span comprises a total of 76 deck units. In the present study, the main span deck is divided into 16 segments, each including 4 or 5 deck units. The damage to the deck members within the same segment is classified as one pattern class. As a result, there are totally 16 pattern classes (\( s = 16 \)). The following modal parameters are taken to constitute the input vector: the natural frequency change ratios of the first four modes, and the three translational components of the first mode vector at the 16 nodes of deck units 2, 7, 12, 17, 22, 27, 32, 36, 41, 45, 50, 55, 60, 65, 70 and 75 (one node for each selected unit). So the length of the PNN input vector is \( p = 4 \times 16 \times 3 = 52 \). In order to obtain the training vectors, for each pattern class two damage scenarios with the damage within the same segment but different units are introduced in the FEM of the bridge and the corresponding modal parameters are evaluated. Each set of the computed modal parameters are then added with a random sequence to form the training vectors.

50 sets of modal parameters are randomly produced for each damage scenario. After entering the noise-polluted training vectors of all pattern classes as weights between the distribution (input) and pattern layers, the PNN for damage localization is configured (trained). When presenting on it a new input vector (test vector) consisting of measured modal data of unknown source, the configured PNN outputs in the summation layer the PDF estimates for each pattern class at the test vector point, and the damaged deck segment is identified by the pattern class with the largest PDF.

The test vectors are produced in a similar way to obtaining the training samples. A total of 16 damage scenarios, with one for each deck segment (pattern class), are examined in the testing phase. The testing damage scenario for each pattern class is incurred at a deck unit different from the training damage scenarios. The analytical modal parameters when incurring damage at each deck segment in turn are calculated and then polluted with random noise to obtain the ‘measured’ test vectors. For each testing damage scenario, 500 sets of noise-corrupted test vectors are produced. Table 3 summarizes the damage location identification results under different noise levels. The integral numbers in the latter five rows of the table show the number (times) of correct identification, out of 500 tests for each damage scenario. The identification accuracy (IA) is defined as the ratio of the total number of correct identification to the total test number. The IA value is 73.75% when the noise level \( \varepsilon = 0.10\% \), 83.68% when \( \varepsilon = 0.08\% \), 90.34% when \( \varepsilon = 0.06\% \), 95.66% when \( \varepsilon = 0.04\% \), and 99.14% when \( \varepsilon = 0.02\% \).

![Architecture of a three-layer PNN](image)

Table 3. Summary of correct identification using PNN technique.

<table>
<thead>
<tr>
<th>Pattern class No.</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
<th>8</th>
<th>9</th>
<th>10</th>
<th>11</th>
<th>12</th>
<th>13</th>
<th>14</th>
<th>15</th>
<th>16</th>
<th>IA ratio</th>
</tr>
</thead>
<tbody>
<tr>
<td>Testing sample No.</td>
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<td>500</td>
<td>500</td>
<td>500</td>
<td>500</td>
<td>500</td>
<td>500</td>
<td>500</td>
<td>500</td>
<td>500</td>
<td>500</td>
<td>500</td>
<td>500</td>
<td>500</td>
<td>500</td>
<td>500</td>
<td>73.75%</td>
</tr>
<tr>
<td>Number of correct localization</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
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<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>( \varepsilon = 0.10% )</td>
<td>302</td>
<td>168</td>
<td>366</td>
<td>246</td>
<td>485</td>
<td>354</td>
<td>480</td>
<td>405</td>
<td>323</td>
<td>364</td>
<td>415</td>
<td>436</td>
<td>349</td>
<td>251</td>
<td>463</td>
<td>493</td>
<td>83.68%</td>
</tr>
<tr>
<td>( \varepsilon = 0.08% )</td>
<td>343</td>
<td>248</td>
<td>444</td>
<td>356</td>
<td>493</td>
<td>434</td>
<td>493</td>
<td>436</td>
<td>351</td>
<td>406</td>
<td>464</td>
<td>461</td>
<td>405</td>
<td>379</td>
<td>484</td>
<td>497</td>
<td>90.34%</td>
</tr>
<tr>
<td>( \varepsilon = 0.06% )</td>
<td>483</td>
<td>339</td>
<td>489</td>
<td>467</td>
<td>464</td>
<td>486</td>
<td>498</td>
<td>472</td>
<td>350</td>
<td>432</td>
<td>477</td>
<td>491</td>
<td>463</td>
<td>395</td>
<td>442</td>
<td>479</td>
<td>95.66%</td>
</tr>
<tr>
<td>( \varepsilon = 0.04% )</td>
<td>431</td>
<td>372</td>
<td>498</td>
<td>476</td>
<td>500</td>
<td>498</td>
<td>500</td>
<td>492</td>
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<td>488</td>
<td>500</td>
<td>500</td>
<td>99.14%</td>
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<tr>
<td>( \varepsilon = 0.02% )</td>
<td>478</td>
<td>470</td>
<td>500</td>
<td>500</td>
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<td>500</td>
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<td>498</td>
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<td>500</td>
<td>500</td>
<td>71</td>
</tr>
</tbody>
</table>
5 CONCLUSIONS

This paper summarized several vibration-based methodologies developed for SHM and damage detection of cable-supported bridges. It has been shown that the auto-associative neural network (AANN) technique is promising for damage alarming in operation with noisy measurement data. Because no structural model is required and only modal frequencies are utilized, this method is applicable to structures of arbitrary complexity. Due to the environmental effects, however, false-positive and false-negative alarms may be issued in applying the AANN technique. Both non-parametric and parametric methods have been developed to eliminate the environmental effects. The AANN technique has been extended to formulate multi-novelty indices for damage region identification. While requiring no structural model, it requires vibration sensors deployed at each of the structural regions. When an accurate structural model is available, the probabilistic neural network (PNN) technique can provide more detailed identification of damage location. For the identification of local damage in large-scale bridges, however, the methods which use dynamic strain measurement are preferred [33].

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