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A Survey on Vibration Based Damage Detection of Bridges under Varying Temperature Effects Using Time Series Analysis

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ABSTRACT: Structural Health Monitoring (SHM) has become a very important area in civil engineering for evaluating the performance of critical civil infrastructure systems such as bridges. One of the most important issues with continuous SHM is the environmental effects (such as temperature, humidity, wind) on the measurement data, which can produce bigger effects in the response of the structures than the damage itself. Damage detection is considered as one of the most important components of SHM and without appropriately considering the environmental factors in the damage detection process, the efficiency and accuracy of this process may be questionable for practical applications. Temperature is considered as one of the most important and influential environmental effects on structures, especially in bridges. In this study, an artificial neural network based approach integrated with a sensor clustering based time series analysis is employed for damage detection under the temperature effects. Damage features from the time series analysis method (will be referred as *DFARX*) can indicate the damage, if there is no presence of detrimental temperature effect. However, if present, temperature effect can lead to false indication of the damage existence in the structure. Neural network damage features (*DFANN*) are used to compensate these effects. Final damage features (*DF*) are computed as absolute difference between these two damage features. The proposed methodology is applied to a footbridge finite element model and it is demonstrated that the method can successfully determine the existence, location and extent of the damage for different types of damage cases under environmental temperature variability, and with different levels of the noise. Finally, recommendations for the future work, as well as the limitations of the proposed methodology are addressed.

KEYWORDS: Structural Health Monitoring (SHM), Time Series Analysis, damage features (*DF*)

I. INTRODUCTION

Due to the complex and progressing problem of deterioration of aging civil infrastructure, Structural Health Monitoring (SHM) has become a very important area in civil engineering for assessing the performance of civil infrastructure systems. SHM is considered to be one of the most critical components of civil infrastructure management for providing an objective, versatile, and innovative decision-making support tool for infrastructure owners and decision-makers to increase the safety and reliability of our infrastructure system. Bridges are among the most critical infrastructures and most of them are reaching or have already reached their life span. In Canada one-third of 75,000 highway bridges are with structural or functional deficiencies (NRCC 2013). Similarly, the most recent Report Card for America's Infrastructure (2013) graded the US infrastructure with a D+, and C+ for bridges (one in nine of the nation's bridges are rated as structurally deficient). Although the SHM is a relatively new concept in bridge engineering community, testing of bridge structures dates before 1900s (ISIS Canada 2001). SHM methodology can be very effective in complementing the visual inspection techniques for determination of

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condition of structures. Condition of the bridge network can be improved by continuous evaluation of bridges using SHM systems. Continuous monitoring of bridges improves safety, reduces response time and it has economic impact on the bridge maintenance practices. Besides the regular continuous monitoring of the structures, SHM can be utilized after the incidental events, such as earthquakes. SHM can then provide relevant information on the new condition of the structure, and determine its operational safety. Structural Health Monitoring (SHM) term can be defined in many ways. For example, Wenzel (2009) indicates that “SHM is the implementation of a damage identification strategy to the civil engineering infrastructure”. Karbhari and Ansari (2009) define SHM as “an attempt at deriving knowledge about the actual condition of a structure”. According to Sohn and Farrar (2000), “SHM is best studied in the context of a statistical pattern recognition paradigm”, composed of the following components:

1. **Operational Evaluation;**
2. **Data Acquisition;**
3. **Feature Extraction;**
4. **Statistical Model Development.**

Operational Evaluation comprises several steps of SHM process. Data acquisition system is specified based on the adopted methodology. Also, damage features are defined for damage detection algorithm.

In *Data Acquisition* part, response of the structure is recorded and transmitted. Cleansing process can also be performed. If necessary, compression of data and data fusion from multiple sources can be conducted. Data is either archived or used simultaneously with the process. Deciding on excitation method is also an important part of data acquisition process. Forced excitation can be used in the form shakers, or other impacting devices. Another option is to use ambient excitation of the structures – pedestrian or vehicular traffic for the bridge structures, wind load, etc.

Feature extraction process determines features that indicate the presence of damage in a structure. Sets of data measured on the structure are transformed to a different form, which can indicate the damage. As an example, damage features in vibration based models can take different forms: coherence functions, modal strain energy, modal assurance criteria, etc.

Final step includes use of *statistical models* in order to separate damage features from damaged and undamaged states. Considering that the damage features can be sensitive to other factors than the damage, normalization can be conducted.

If damage detection methodology includes input data and desired output data, that type of learning is considered supervised learning. Unsupervised learning refers to methodologies with input data only. For bridge structures, it is usually very impractical to retrieve desired output data, therefore unsupervised learning is preferred.

Another classification of methods can be done depending on whether the physical models or models based on data are used (Aktan et al. 1999; Worden and Manson 2007). Former group of methods belongs to the model-based methods, and the latter one to data-driven methods. For example, finite element based models belong to the first group, considering that they are based on physical properties of the structure. On the other side, data-driven methods depend on data from the measurements only. Considering that there is no knowledge needed on structural system in second group of methods, these methods are more practical for continuous monitoring of bridges, even though model-based methods may provide more information in certain cases.

Considering that all materials contain some defects (Worden et al. 2007) that can propagate during the lifetime of the structure, detecting these defects is of major importance for safe and proper service of the structures. Therefore, damage detection is considered as one of the most important components of SHM. In damage detection methods, global or local techniques can be used. The issue with the local techniques is that the approximate location of the damage should be known in advance, which is not always practical. On the other hand, such issues are minimized with vibration based global monitoring methods. These methods have been employed for a few decades (Doebbling et al. 1996; Farrar and Jauregui 1998; Guan 2006; Fan and Qiao 2011; Brownjohn et al. 2011). They are based on the fact that modal characteristics of the structure are related to the physical characteristics of the structure

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(stiffness, mass, damping) and that any change in these characteristics would cause change in modal properties, causing the change in dynamic response of the structure. Vibration response of the structure is usually measured at several locations, and this data is then used for determination of modal parameters of the structure (or other damage features based on the dynamic characteristics of the structure), which can then be used for damage detection process.

One of the most important issues with vibration based continuous SHM is the environmental effects on the measurement data. This is especially true for civil infrastructure systems, such as bridges, where environmental factors, such as temperature, humidity and wind, can produce bigger effects in the response of the structure than the damage itself (Sohn 2007; Sohn and Oh 2009). Considering that the real damage can be masked by the environmental effects, this can lead to false conclusions on the damage. In order to compensate environmental effects, one can use the measurements of the environmental data, or perform the analysis without direct measurement of these parameters. If measured, parameters should be determined from a wide range of different environmental conditions in order to comprehensively define baseline condition of the structure (Sohn 2007).

Temperature is considered the most significant and influential environmental effect on bridges. Temperature variation alters dynamic characteristics, such as natural frequencies, of the structure (Sohn et al. 1999), and affects the performance of the vibration based methodologies. As an example, Cornwell et al. (1999) presented that for the single span bridge structure, modal frequencies varied up to 6% over a 24-hour period. Temperature changes mainly affect the stiffness of the structure (Wood 1992; Khanukhov et al. 1986; Sabeur et al. 2007), and support conditions (Moorty and Roeder 1992; Sohn 2007; Siddique et al. 2007). Besides these two effects, temperature effects can cause additional thermal stresses in structures, which can also alter the vibration response of the structure. Without appropriately considering the environmental factors in the damage detection process, the efficiency and accuracy of this process may be questionable for practical applications.

Another difficulty for assessing the temperature effects on modal properties of structures is the non-uniform distribution of temperature in the structure, especially bridges. Bridges are usually designed as unique structures, with specific boundary conditions, geometry, location and types of loads (Wenzel 2009). Temperature distribution in bridges depends on orientation, shape and environment of the bridge structure. Therefore, this distribution will also be specific for different bridges. Moreover, surface temperatures are usually different compared to the inner temperature of the elements, because of the thermal inertia effect. It is also determined that temperature gradients provided in the codes are usually smaller than the measured temperature gradients for stiff structures (Wenzel 2009). All of these effects contribute to the randomness of the temperature distribution in the structure. Besides the environmental effects, operational effects, such as traffic, can have disturbing effect on the vibration measurements.

1.2 Objectives

As discussed above, vibration based damage detection methods can experience detrimental effects from variable environmental factors, since change in these factors influences dynamic response of the structure, and therefore alters the measured data. Therefore, in order to successfully perform damage detection process, these effects must be minimized. Temperature is considered as one of the most common and influential environmental effect. Thus, the objective of this thesis is to develop a damage detection framework based on the vibration response of the structure, where temperature effects on damage detection process are compensated. The developed framework uses a sensor clustering based time series analysis method for damage detection (Gül 2011) along with artificial neural networks for temperature compensation. After discussing the theoretical developments, the methodology is tested using the finite element of a footbridge.

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II. LITERATURE REVIEW

Literature review of the most relevant structural health monitoring publications is presented in this chapter. Considering that this thesis focuses on temperature effect compensation in damage detection processes, papers regarding the damage detection methodologies are presented first. Following are the papers which analyze the environmental effects on bridges and damage detection methods. Finally, publications investigating compensation of environmental effects are presented.

2.1 Literature Review of Methods for Damage Detection

Damage detection is considered as one of the most important components of SHM. A variety of damage detection methods is presented in this section. According to Rytter (1993), damage detection methods can be used for different levels of assessment:

Level 1: Is there damage in the system (existence)?

Level 2: Where is the damage in the system (location)?

Level 3: How severe is the damage (extent)?

Level 4: How much useful (safe) life remains (prognosis)?

Pandey et al. (1991) analyzed cantilever and simply supported beam models, and concluded that changes in curvatures of the mode shapes can indicate the location of the damage. Hamey et al. (2004) confirmed that damage detection process can be conducted with curvature of the modes, which can be measured by the piezoelectric sensors.

Nakamura et al. (1998) investigated the application of neural-networks for damage detection process in a steel building structure. The structure was damaged under earthquake loads in Kobe, Japan in 1995. Vibration measurements were performed after the damage, and also after the repairs. State of the structure after the repairs was used as a baseline state. Neural-network based methodology was able to successfully identify locations of the damages that were subsequently repaired afterwards.

Lamb waves, as non-destructive methods, have also been used for damage detection algorithms. Lamb waves are used along with the piezoelectric sensors, which are power efficient. Monnier et al. (2000) analyzed a plate-like composite structure for localization of flaws. They indicated that sensitivity of lamb waves with regards to the type of the damage can be improved with adjusting the excitation of the sensor. Kessler (2002) indicated that lamb waves are more sensitive to local damage, compared to the frequency response methods. It was also concluded that the shortcoming of these methods is that they require a mechanism for wave propagation. Sohn et al. (2003) successfully detected delamination damage case on composite plate with variable temperature effects and boundary conditions.

Yam et al. (2003) investigated a damage detection methodology applied to composite sandwich plate structures with crack damage. The methodology employed vibration data, wavelet transform and artificial neural networks (ANN). Damage features were based on the energy variation of wavelet signals before and after the damage, where neural networks were used for statistical pattern recognition. It was indicated that excitation signals should be consistent for the baseline and damaged case, and should contain sufficient number of frequency components.

Giraldo et al. (2006) analyzed an analytical model of a benchmark structure using the vibration data along with the applied noise. Structural properties were obtained from this data, and principal component analysis (PCA) was then applied. Damage indicator in this method is based on the residual error of PCA method. Damage was simulated in the analytical model as a loss of stiffness. It was concluded that particular damage detection techniques may not be applicable to all types of damages in different structures.

Bakhary et al. (2007) employed an ANN algorithm along with the substructure technique, in order to adapt the algorithm to be more sensitive to local damage in two span concrete slab model. With this method, ANN models were defined for each part of the substructure, and all of the substructure parts were analyzed progressively. ANN used modal frequencies and shapes as an input data. Eventually, the method successfully detected the damage, which was applied as a reduction of the local stiffness along the slab.

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Mehrjoo et al. (2008) used a backpropagation neural network for the analysis of damage cases for joints of a truss bridge. Input data comprised natural frequencies and modeshapes of the structure. It was indicated that five modes were sufficient for this algorithm to function, and that the average errors for the testing data were 1%.

Gül and Catbas (2009) investigated application of statistical pattern recognition based methods for damage detection process of a simply supported steel beam and a steel grid laboratory structure. AR models were defined based on the obtained vibration data, and were used along with the Mahalanobis distance in order to retrieve damage indicators for this method. Methodology was successful for most of the damage cases. Importance of proper determination of threshold values for damage indicators was emphasized.

Gül and Catbas (2011) introduced a time series analysis based damage detection algorithm. This process was based on determining Auto-Regressive models with exogenous input (ARX) from the free vibration response of the structure. Important feature of this methodology is that the sensor nodes were grouped in different clusters. ARX models were then defined by vibration data from neighbour sensors within one sensor cluster, in order to predict behaviour of the reference sensor in the cluster. Damage features used in this methodology were the fit ratios of the ARX model. This methodology was applied to a four DOF numerical model, and to the steel grid laboratory model. It successfully determined the existence, location and extent of the damage (levels 1, 2 & 3 by Rytter (1993)).

Shiradhonkar and Shrikhande (2011) employed a finite element model updating method for determination of damage location in a moment resistant frame structure. Vibration data from the structure, initialized by several strong earthquakes, was used to obtain modal parameters needed for the updating algorithm. Possible effects of the noise on the updating process were also discussed.

Samali et al. (2012) investigated combination of artificial neural networks (ANN), frequency response functions (FRF) & principal component analysis (PCA) as a vibration based damage detection process. PCA was utilized to determine principal components of the difference between FRF components in damaged and undamaged state. PCA was also employed to compensate the noise effects of 10% applied in this study. ANN was finally used for damage detection, where FRFs from different locations in the baseline model were used for training of the network, and then for the simulation process. Similar algorithms were employed by Li et al. (2011), Dackermann and Samali (2013) and Bandara et al. (2014).

Shu et al. (2013) analyzed a finite element model of a simply supported railway bridge. Acceleration and displacement data from the bridge were used for determination of the changes of variances and covariances between baseline and damaged condition of the structure. A backpropagation neural network was then trained with the data from pre-defined damage cases in order to successfully determine location and extent of the damage. Influence of noise and train properties is indicated. The methodology could successfully detect damage cases with reduction of element stiffness above 10%.

Fassois and Kopsaftopoulos (2013) discussed different statistical time series methods based on the vibration data, and applied them to a laboratory truss structure for damage detection. Time series methods were classified as non-parametric and parametric based methods, and properties of both groups were analyzed. It was indicated that although parametric based methods were more effective with damage detection, they required parameter estimation to be conducted more accurately and elaborately. It was also concluded that adequate damage threshold should be determined in order to properly conduct the damage detection process. Finally, importance of using random excitation/vibration based data was emphasized.

Liu et al. (2015) employed guided ultrasonic waves along with the singular value decomposition (SVD) method for damage detection in a pipeline structure. Field experimental data of a hot water piping system had been collected for a period of seven months. Damage detection process was based on the orthogonality between singular vectors from damage and environmental effects. Method was able to detect the damage from the mass scatterer.

As indicated in this chapter, a variety of damage detection methods can be employed in SHM process. Every type of methodology experiences some limitations. Some of the localized methods (such as non-destructive evaluation NDE methods) need to know the location of the damage in advance. Other global methods, e.g. based on the modal parameters of the structure, do not have this issue. However, methods that are based on modal parameters can be

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conducted at only several points in the structure. Challenge with the global methods is that damage usually occurs locally, which means that lower frequency response of the structure, usually measured during ambient excitation, may not be significantly affected with this damage.

2.2 Literature Review of Environmental Effects on the Behaviour of Bridges and Damage Detection Process

As already emphasized, environmental effects can have detrimental effects on damage detection methodologies. Here, different studies are listed, where effects of the environmental variability in bridges and damage detection of structures are indicated.

Moorty and Roeder (1992) examined temperature dependent bridge movements. It was concluded that increase in bridge temperature causes uniform expansion in all directions of the bridge. Considering that some bearings allow movement only in one direction, large thermal forces can be introduced to the structure from temperature variation. Also, condition of the bearing is an important factor, considering that the deterioration of the supports can increase stiffness of the bearings and resistance to movement, which can cause increase of the thermal forces in the bridge.

Wahab and De Roeck (1997) concluded that the temperature variation mostly influences the elasticity modulus in the bridge structure. Also, frequency variation of 4-5% was indicated due to 15°C temperature variation. Alampalli (1998) investigated support freezing effect at the bridge structure, and concluded that this condition can have bigger effects on the change of modal frequencies than the damage cases.

Modal frequencies of the Alamosa Canyon Bridge (Doebbling et al. 2000; Cornwell et al. 1999) varied approximately 6% during a 24 hour test period. Modal frequencies varied mostly because of the material changes due to the temperature change, and due to the changes in the boundary conditions, considering that debris in the support location obstructed free expansion of the joints.

Fujino et al. (2000) analyzed wind effects on a 720m suspension bridge, and compared it to the wind tunnel experiments. Natural frequency variation was not confirmed from the field measurements, considering that the natural frequency decreased with the increase of the wind speed up to 14.9m/s. However, it was expected that natural frequency would increase after some level of the wind speed. Damping ratio significantly decreased up to a wind speed of 8m/s, and then it behaved in increasing manner, as in the wind tunnel experiment.

Fu and DeWolf (2001) analyzed a two span steel girder bridge with temperature variation. FE modeling was used to verify the field measurements, where vibration data was used for the model calibration. Increase of the natural frequencies occurred with the drop of the temperature. It was also concluded that increased friction in the bearings for the lower temperatures partly restrained rotation of the supports, causing axial tensions forces in the structure. With the temperature increase from -17.8°C to 15.6°C, first three natural frequencies decreased by 12.3%, 16.8%, and 8.96%.

Simonsen et al. (2002) investigated change of resilient modulus of coarse and fine grained subgrade soils due to temperature change. It was concluded that all soils experience reduction of the modulus due to the freeze-thaw process, therefore affecting the support conditions of structures.

Breccolotti et al. (2004) analyzed a simply supported internal span of the reinforced concrete bridge over the Tiber River. They concluded that level of frequency change due to the damage and temperature variation is comparable, which means that temperature effects can mask the effects of the damage. They also indicated that methods based on pattern recognition, statistical analysis and neural networks may be more efficient for damage detection, compared to the frequency based methods.

Catbas et al. (2008) analyzed reliability of cantilever truss bridge, with one year of temperature monitoring data. During that year temperature values varied between 15°F and 90°F. It was determined that annual peak-to-peak strain differential is ten times higher than strains caused by the traffic, which demonstrates the importance of temperature influence regarding the system reliability. It was also concluded that monitoring of the structure should be performed at bigger number of locations for better determination of temperature.

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Zhou et al. (2008) performed damage detection on cable-stayed Ting Kau Bridge with relative flexibility change (RFC) index, which was formulated from modal frequencies and mode shape vectors of the structure. Seventeen damage cases were analyzed, incorporating measurement noise, traffic and temperature effects. While RFC index identified damage location successfully with no ambient effects, it encountered difficulties when these effects were added. Finally, it was concluded that data should be retrieved from a range of ambient conditions for successful elimination of ambient effects.

Xu and Wu (2007) investigated a long-span cable stayed bridge and its mode shapes, as well as frequency variability due to the temperature changes. It was indicated that uniform temperature variation in a structure can be caused by seasonal weather changes, and non-uniform temperature distribution by radiation of sunshine during the day. Frequency change due to temperature variation from 40°C to -20°C was around 2%. It is also mentioned that asymmetric temperature distribution causes similar variation behaviour of frequency and mode shape variation as with the symmetric temperature distribution. Finally, it was determined that temperature variation causes bigger frequency changes than damage of cables and girders in the structure.

Pham (2009) analyzed the Attridge Drive Overpass in Saskatoon, Saskatchewan. Due to the temperature change from -12°C to 40°C, first three natural frequencies decreased by 8.3 %, 12.3 %, and 12 %. It was indicated that the major factor for frequency change was the reduction of the modulus of elasticity of bridge materials. Considering that the asphalt layer was present, relationship between the temperature variability and frequency change was bilinear.

Shoukry et al. (2009) analyzed the environmental effects on Star City Bridge in West Virginia. Temperature varied between -8°C and +38°C. It was concluded that non-uniform temperature gradient across the bridge was around 6.5°C.

III. PROPOSED METHODOLOGY FOR DAMAGE DETECTION UNDER TEMPERATURE EFFECTS

As already indicated in the previous chapters, the objective of this thesis is to develop a damage detection algorithm based on the vibration response of a structure, where temperature effects on damage detection process are successfully compensated. In order to assess the damage under temperature effects, a sensor clustering based time series analysis method is employed along with backpropagation algorithm based artificial neural networks. Time series based damage detection algorithm described in Chapter 3.1 was originally proposed by Gül and Catbas (2011). It employs free vibration output-only data in order to define ARX models for different sensor locations. This methodology introduces a novelty approach where sensors are grouped in different sensor clusters, which are composed of one reference channel and other neighbour channels. Output data of the neighbour channels is used for predicting the behaviour of the reference channel. Changes in these models indicate the existence, location and severity of the damage in structure. Damage features are defined as the fit ratio of the ARX models (which will be referred as *DFARX*) and are sensitive to damage. However, they are also sensitive to the effects of temperature on the output vibration data of the structure. Therefore, effects of the temperature on vibrational properties of the structure must be compensated for efficient damage detection process.

Final damage features are presented in Chapter 3.3. They are determined as absolute value of the difference between the damage features from Chapter 3.1 and from Chapter 3.2. In order to prove its effectiveness, this methodology is applied to a footbridge FE model with five damage cases. Characteristics of the model are presented in Chapter 4, and the results are explained and discussed in Chapter 5.

3.1 Time Series Modeling for Structural Dynamics

Time series modeling enables creation of systems based on sequence of data points in time, measured at uniform time intervals. Time series models can be applied to various problems in SHM. In this research, they are utilized

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for defining dynamic behaviour of the structure. Time series models that are relevant to this research are Auto-Regressive Moving Average model with eXogenous input (ARMAX model) and the Auto-Regressive model with eXogenous input (ARX model). A more detailed description of these models is given in (Ljung 1999; Box et al. 2013).

Linear time series difference equation is shown in Eq. 3.1 (Ljung 1999), which represents the relationship of the input, output and the error terms:

$$y(t)+a_1 y(t-1)+\dots+a_{n_a} y(t-n_a)=$$

$$b_1 u(t-1)+\dots+b_{n_b} u(t-n_b)+e(t)+c_1 e(t-1)+\dots+c_{n_c} e(t-n_c)$$
(3.1)

Where $y(t)$ is the output of the model, $u(t)$ is the input to the model, and $e(t)$ is the error term. The unknown parameters of the model are a_i , b_i , and c_i , and the model orders are n_a , n_b , and n_c . A reduced form of this expression is given in Eq. 3.2, and it represents an

ARMAX model:

$$A(q)y(t)=B(q)u(t)+C(q)e(t)$$
(3.2)

IV. CONCLUSION

In this thesis, a new framework to compensate detrimental temperature effects in damage detection process is presented. For the proposed framework, a time series analysis based damage detection method is employed along with back propagation artificial neural networks for damage detection. A finite element model of a steel footbridge structure with concrete deck and with two equal spans is used for verification of the developed methodology. Five damage cases are applied to the model, along with variable temperature effects with a range of -25°C and 55°C . These temperature effects cause change of elastic modulus for steel and concrete material, as well as additional axial forces in the structure. These two factors then alter the dynamic response of the structure. In the time series analysis part of the method, vibration data of the structure is used to define ARX models with sensor clustering methodology, where neighbor sensors in particular cluster are used to predict the vibration behavior of the reference sensor. Considering that time series analysis part of this method employs vibration data for damage detection, temperature variability affects the output of this method. It is demonstrated in Chapter 5 that damage features from the time series analysis part of the methods (*DFARX*) clearly indicate the location and extent of the damage for all five damage cases without the temperature effects. However, when temperature effects are assigned to the system, it is shown that damage is not clearly indicated with these damage features. In order to compensate the temperature effects, back propagation algorithm for neural networks is then applied as a next step. Neural networks are first trained with the *DFARX* from the healthy state with different temperature effects, where the input data consists of temperature values for three groups of elements at the bridge structure. It is presented in Chapter 5 that this methodology can successfully compensate temperature effects for all damage cases introduced to the footbridge finite element model without the noise effects and for most of the cases with the introduction of the noise effect. To the best of knowledge of the author, it is the first methodology capable of identifying and locating damage under temperature effects by using output only vibration data.

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