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ELIMINATING ENVIRONMENTAL INFLUENCES IN VIBRATION-BASED DAMAGE DETECTION USING ARMAX RESIDUAL ERROR AND ARTIFICIAL NEURAL NETWORKS

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ABSTRACT

Despite offering a great promise for continuous and automated monitoring of civil infrastructure systems, vibration-based damage detection methods may yield false positives and negatives due to environmental and/or operational effects. This paper presents a method based on ARMAX residual error in conjunction with Artificial Neural Networks (ANNs) to eliminate the environmental effects from damage detection process. A finite element model of a bridge type structure was simulated with different damage scenarios under various temperatures. Damage features obtained from statistical process on ARMAX residual errors were then compared between with and without environmental effects. Artificial neural networks were trained to learn and predict damage features due to temperature change only, by subtracting which the final damage feature was obtained. It is shown that both damage location and damage severity can be accurately identified.

Keywords: Structural Health Monitoring, damage detection, environmental effects, time series analysis, ARMAX residual, artificial neural network

1. INTRODUCTION

Structural health monitoring (SHM) techniques have rapidly been developing in the last two decades, with a motivation for assisting the infrastructure owners with their decision-making offering improved performance and cost savings. One of the main topics in SHM is damage detection, localization and quantification (Bernal et al., 2004; Fan et al., 2011). A large number of vibration-based methods have been proposed during the last decades (Bernal et al., 2004; Ko et al., 2005; Mattson et al., 2006; Mei), which are based on the fact that the dynamic characteristics of the structure will change with physical properties of the structure (mass, stiffness, damping).

Time series based analysis is a widely used category of techniques in SHM, among which derivatives of autoregressive series models (AR) can be used to approximate the structure vibration. Damage detection techniques based on AR model can be divided into two categories, coefficient-based and residual error-based (Mattson et al., 2006; Mei). For example, Nair and Kiremidjian investigated a sensitive damage indicator with the first three AR coefficients of autoregressive moving average model (ARMA) (Nair et al., 2006). By means of analysis on strain data in time history, Omenzetter et al. proposed a damage detection method based on changes in coefficients of ARMA model (Omenzetter et al., 2006). Gul and Catbas proposed an algorithm based on fit ratio of the ARX models fit to different sensor clusters (Gul et al., 2011). By using mean value and the variance of AR model residual error, Fanning proposed a new statistical control approach for damage detection (Fanning et al., 2001).

However, one of the most significant problems in real life applications of vibration-based SHM techniques is the effects of the environmental changes on the structure. As is known, damage will change the vibration response of the structure; however, environmental effects can also change the dynamic properties of the structure. This may lead to false negatives and positives in damage detection process because the damage may be masked by environmental changes (Moser et al., 2011; Peeters et al., 2001). Many investigations proved that temperature is the most influential environmental effect causing the change in vibration properties of bridges (Khanukhov et al., 1986; Peeters et al., 2001; H. Zhou et al., 2010), the variation of natural frequencies due to temperature change only can reach as much as 5% to 10% for highway bridges, which are higher than the changes caused by damage or deterioration in structures (Ko et al., 2005). However, there are many challenges to understand the environmental effects (G. Zhou et al., 2013). The nonuniform temperature distribution and time-dependent transmission is quite complicated, which results in asynchronous changes in physical parameter in the structure. The sizes of the members in a bridge can change under different temperatures. In addition, some of the material properties that are used in calculating vibration properties, such as Young's modulus and shear modulus, may also change with variation in temperature. Finally, the boundary conditions, such as supports and joints, may change due to daily or seasonal temperature changes and the thermal stresses and stress redistributions may highly affect the dynamic properties.

The challenges caused by environmental effects leads to false positives and negatives in traditional vibration-based damage detection methods, including time series analysis (Hios et al., 2014; Kostic; Moser et al., 2011). To avoid or minimize the impacts of environmental complexity on the performance of damage detection methods, many types of approaches and tools have been developed (Ko et al., 2005; Kostic; G. Zhou et al., 2013). One of the most promising tools is artificial neural network (ANN) which is able to learn complex relationships between different types of inputs and outputs. Based on real life measurements and FE model of Ting Kau Bridge, auto-associative neural network (AANN) and back propagation neural network was used to determine the natural frequencies and damage detection (H. Zhou et al., 2010, 2011). As a powerful tool, ANN can easily be combined with other methods. For example, support vector machine and ANN were combined to get the relationship between temperature and thermal response of a concrete footbridge (Kromanis et al., 2014). The parameters of ARX model were used to feed the ANN by Sohn to detect damage, but only indicated the damage existence (Sohn et al., 2002).

2. METHODOLOGY

2.1 Time series modelling for dynamics of Structures

For a structure with N degrees of freedom (DOF), the equation of motion is

[1] $$[\mathbf{M}]\ddot{\mathbf{x}}(t)+[\mathbf{C}]\dot{\mathbf{x}}(t)+[\mathbf{K}]\mathbf{x}(t)=\mathbf{f}(t)$$

where $[\mathbf{M}]$ is the mass matrix, $[\mathbf{C}]$ is the damping matrix, $[\mathbf{K}]$ is the stiffness matrix, and $\mathbf{f}(t)$ is the force vector which is 0 if it is under free vibration.

As proposed by Gül and Catbas (Gul et al., 2011), the acceleration of any DOF can be obtained by its neighbor DOFs in one sensor cluster. Figure 1 illustrates the anbasic example of how sensors are grouped as a cluster, where the reference channel is 1, with 2, 7 and 8 being the neighbor channels. By measuring the sequence of data points in time with uniform time interval, time series analysis can be applied to many problems in SHM. The time series model used in this paper is Auto-Regressive Moving Average model with eXogenous input (ARMAX). In general, the structure of an ARMAX model that describes the relation of input, output and error terms is:

[2] $$A(q)y(t)=B(q)u(t-n_k)+C(q)e(t)$$

where $y(t)$ is the output of the model at time t, $u(t)$ is the input, $e(t)$ is the error term, n_k is called the dead time in the system which is the number of input samples that occur before input affects output. $A(q)$, $B(q)$ and $C(q)$ are polynomials with back shift operator q.

If the acceleration of different locations of a structure are considered as time series samples, the acceleration of the ith channel (reference channel) can be defined as $y(t)$ in Eq. 2, and the acceleration of neighbor channels can be defined as $u(t)$, based on the assumption that the model is inherently regard displacement and velocity as dependent variables on acceleration.

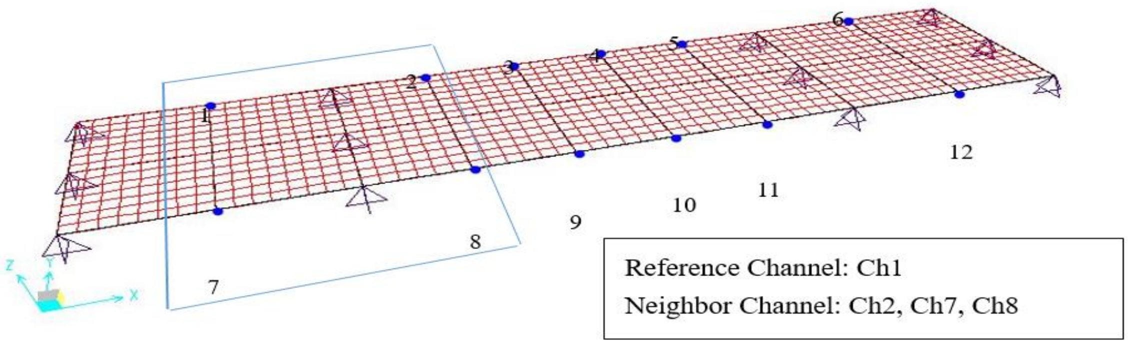


Figure 1: Illustration of sensor clustering

When these ARMAX models are constructed for both undamaged and damaged cased, the predicted output acceleration of each reference channels, i.e., the residual error e, can be obtained by the following equation,

[3] $$\begin{aligned} e_h &= y_h(t) - \hat{y}_h(t) \\ e_d &= y_d(t) - \hat{y}_d(t) \end{aligned}$$

where h and d represent for healthy and damaged cases, respectively, the hat ^ means the output is predicted output. Then the residual errors are normalized to remove the influence of response amplitude.

[4] $$\begin{aligned} \bar{e}_h &= e_h / \left\| y_h(t) \right\| \\ \bar{e}_d &= e_d / \left\| y_d(t) \right\| \end{aligned}$$

2.2 Statistical process on ARMAX residual error

To extract more information, the empirical cumulative distribute function of normalized residual error need to be calculated by Eq.5,

[5] $$F(t) = \frac{\text{number of elements in the sample } \le e}{n} = \frac{1}{n}\sum_{i=1}^{n} 1_{e_i \le e}$$

where 1_X is the event indicator for X, that is, for a fixed value of error e, the indicator $1_{e_i \le e}$ is a Bernoulli random variable with parameter $p = F(e)$.

In statistics, the Kolmogorov-Smirnov test (K-S test) is a nonparametric test of the equality of continuous, one-dimensional probability distributions to compare one sample with reference or compare two samples.

The K-S test considers the null hypothesis that the cumulative distribution function or empirical cumulative distribution function of the target sample is the same as the CDF or ECDF of a reference sample, or assess whether two sample have the same CDF or ECDF (El Bantli et al., 2001; Wang et al., 2009). K-S test also quantifies a distance between the empirical distribution function of target samples with empirical distribution function of reference samples, or the distance between the empirical distribution functions of two samples. The distance can be calculated as,

[6] $$D_0 = \sup_{-\infty<e<\infty} \left| F_{N1}^{h}(e) - F_{N2}^{d}(e) \right|$$

where $N1$ and $N2$ are the length of data of the two samples, if they are different, then N is defined as

[7] $$N = \frac{N_1 N_2}{N_1 + N_2}$$

If $D^* = \sqrt{N}D$ is greater than the corresponding critical level, the null hypothesis that the two distributions are equal, at significant level α , is rejected.

2.3 Back propagation neural network

Back propagation neural network (BPNN) was first introduced into artificial neural network (ANN) for multilayer perceptron (MLP), where they proposed adjustment of the weights from input layer to hidden layer. In this paper, two different neural networks were constructed, one of which was trained to understand the relationship between temperature and the distance D_0 from K-S test, and the other is to simulate the relationship between natural frequencies and temperature.

2.4 Determination of damage feature

From 2.1, when the ARMAX models are defined, the model will not predict output with a good fit in damaged cases, the residual will carry different information from healthy state. Then the distance D_0 will change, as well as natural frequencies. The damage feature from ARMAX (DF_{ARMAX}) only is expressed as,

[8] $$DF_{ARMAX} = D_0$$

where D_0 is the distance between two empirical distribution functions.

The damage feature above reflects the changes from two parts: one is due to damage and the other is caused by change in temperature. Then, to compensate the temperature effects, the two neural networks were trained to predict the distance D_0 in healthy state at random temperature, denoted as D_{0_ANN} , and the difference in natural frequencies of healthy state at different temperature, Δf . The final damage feature can be defined as

[9] $$DF = \left| DF_{ARMAX} - DF_{0\_ANN} \right| \left| f_h^2 - \left| f_d - \Delta f \right|^2 \right|$$

3. VERIFICATION BY NUMERICAL SIMULATION

3.1 Description of finite element model

As shown in Figure 1, a finite element model (FEM) which is a 3-span bridge-type structure with 6mm steel deck was created to verify the methodology proposed above. The information of the model was listed in Table 1.

It is believed that the change in modulus of elasticity due to temperature change is one of the reasons for the change in dynamic properties due to temperature. The relationship between element temperature and modulus of elasiticity of steel is shown in Figure 2.

Table 1: The physical details of the FE model

Span Arrangement	**Structure Type**	**Girder Section**	**Deck Thickness**
1.5m+3m+1.5m	Continuous Simply Supported	S3X5.7	6mm
Girder Material	**Deck Material**	**Excitation**	
Steel Grade 350	Steel Grade 350	Impact forces	

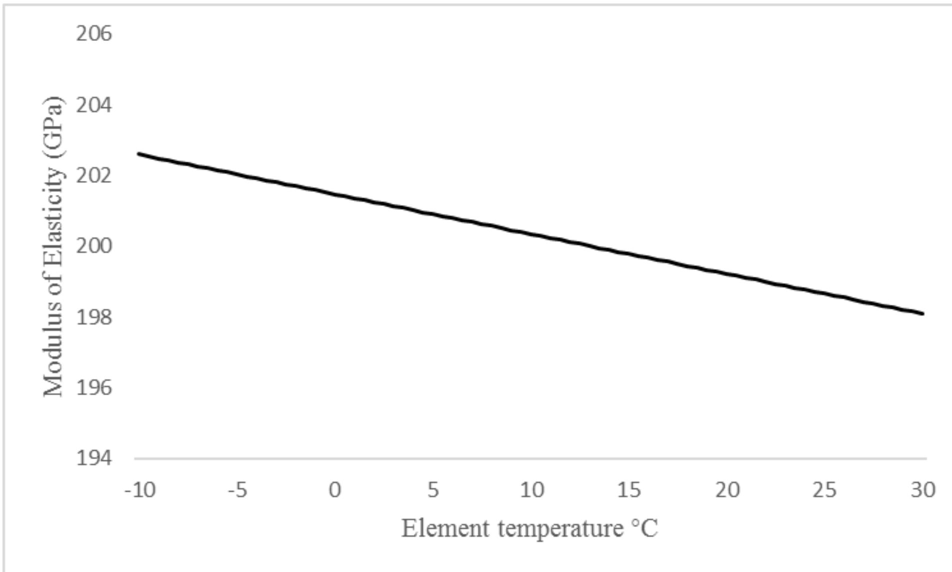


Figure 2: Relationship between element temeprature and modulus of elasticity of steel

12 channels were defined to measure the acceleration at 12 different locations, and sensors were grouped by means of the method described in 2.1. Two damage cases, where the modulus of elasticity in a transverse area between Ch4&Ch5 and Ch10&Ch11 (shown in Figure 3) were reduced, were applied to the model. The first case is 30% reduction in Young's Modulus (DC1) and the other is 50% (DC2).

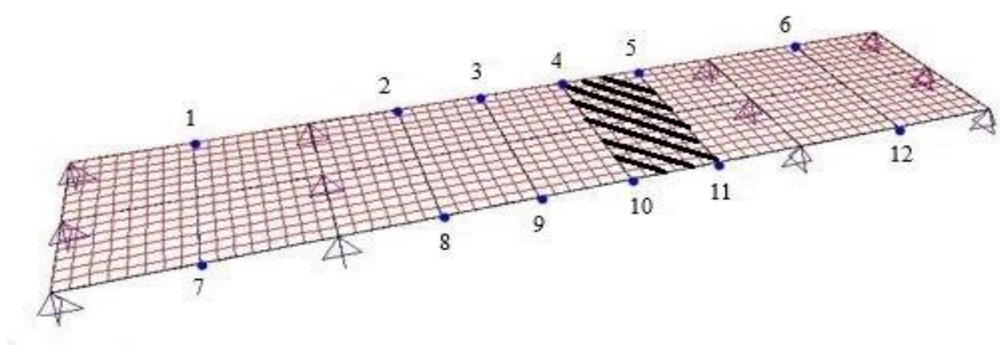


Figure 3: Damage Location (Reduce Young's Modulus in shaded area for 30% and 50%)

3.2 Modal properties and damage feature from ARMAX model

Damage features for DC1 in Damage Case 1 and 2, as shown in Figure 4, are obtained from damage cases without any temperature effects (at baseline temperature). It can be easily found that the damage features at channels 4 and 5, as well as channels 10 and 11 reach its highest values, which clearly indicates that the damage location. However, if temperature effects were added into the structure, the 4 groups of damage features at random temperatures cannot detect the damage location, nor damage severity accurately, as illustrated in Figure 5.

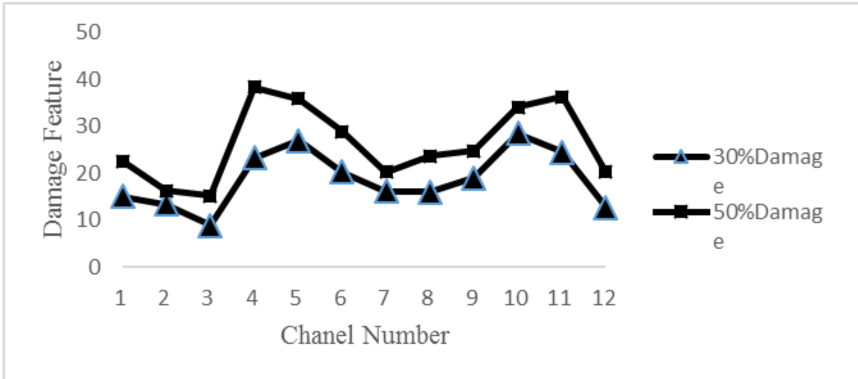
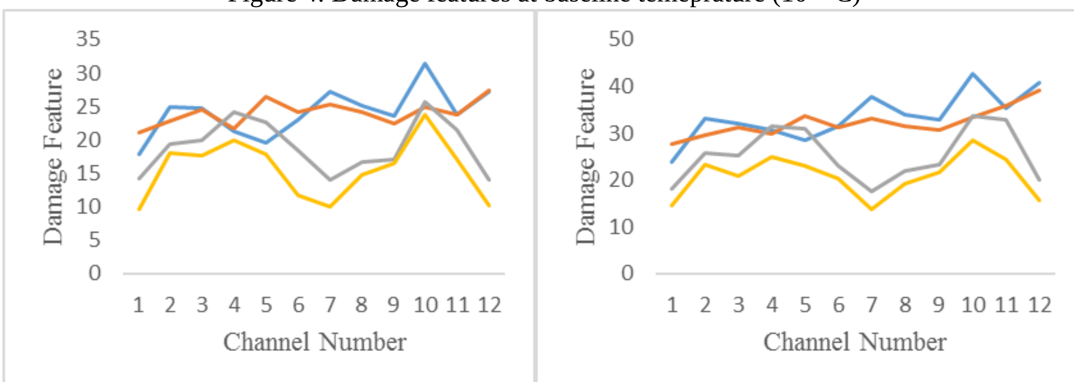


Figure 4: Damage features at baseline temeprature (10° C)



a) Damage feature for DC1 b) damage feature for DC2

Figure 5: Damage features at 4 random temperatures

3.3 Artificial neural network

The first neural network ANN1 was used to learn the relationship between natural frequencies and element temperature. It has 1 input node which was fed by temperature value and 12 output nodes which gave the natural frequencies of the first twelve modes, and was trained by Levenerg-Marquardt (LM) method. In Figure 6, the identified fundamental frequency from finite element model and the predicted fundamental frequency from ANN1 were compared in first half of the figure, which showed a good performance and correspondence of prediction. The second half of the figure shows the predicted frequencies by ANN1 only.

Undamaged and damaged models were calculated 500 times at 500 random temperatures to yield the time series data, from which the initial damage indicators were obtained. The initial damage indicators, which are K-S distance, calculated by ARMAX model due to temperature change only were used to train the second neural network (ANN2), which has 1 input node, 1 output node and 10 hidden nodes. The output yielded by ANN2 were plotted in Figure 7, where in order to show clearly, only 10 outputs are shown.

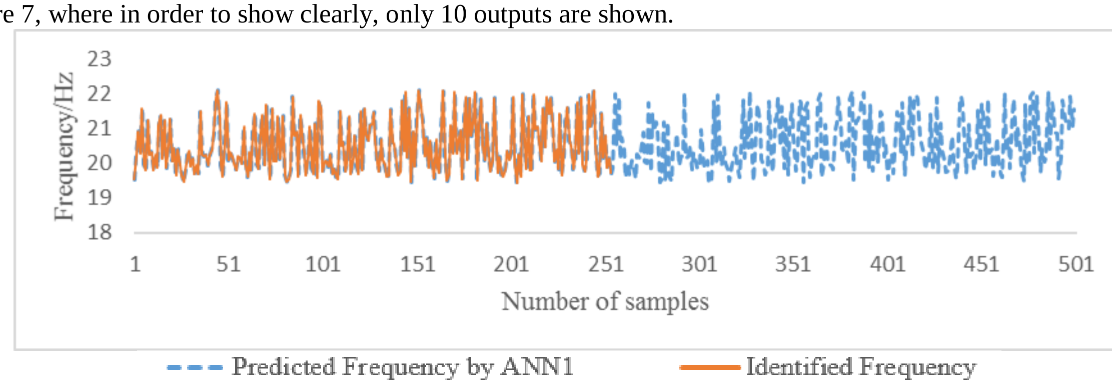


Figure 6: Predicted Frequency vs Identified Frequency (First Mode)

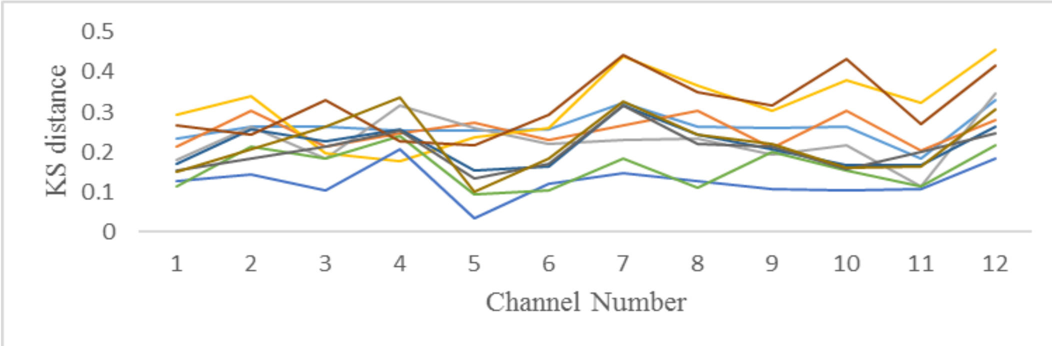
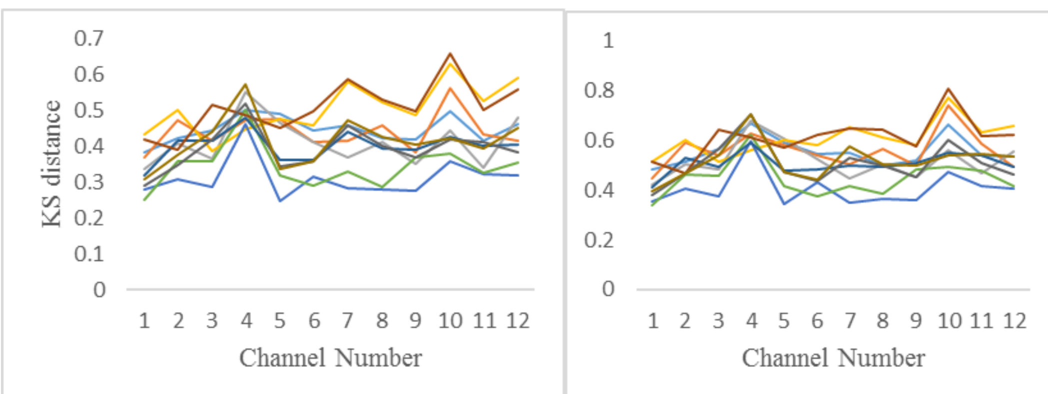


Figure 7: K-S distance of ARMAX residuals due to temperature change only

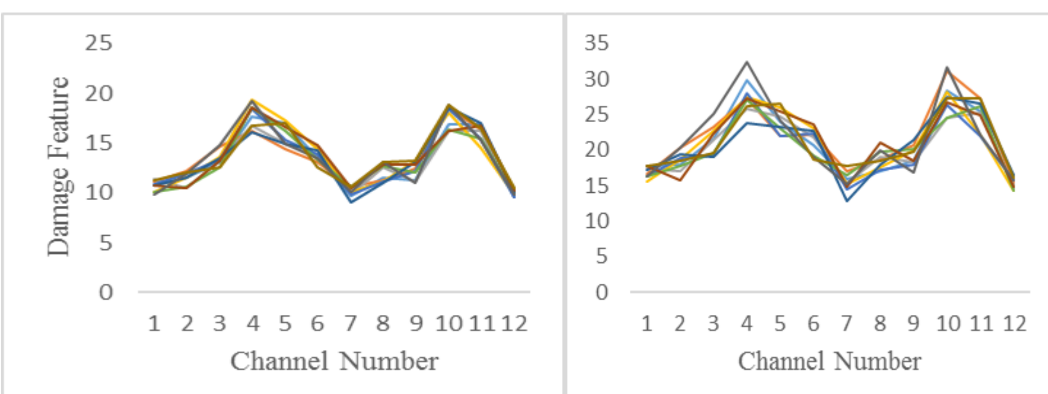
3.4 Eliminating temperature effects

By using the approach discussed above, the final damage feature was calculated by subtracting the damage feature due to temperature change only from that due to damage under environmental effects. Noticing that temperature effects change both the performance of ARMAX models and natural frequencies, it is necessary to eliminate temperature influence on both parameters, which is explained in Eq. 9. To show clearly, Figure 8 plots the KS distance from ARMAX models at 10 random temperatures for the two damage cases, while the final DFs are shown in Figure 9. It is clearly to see that after the elimination of temperature effects, the final damage features can indicate both damage location and damage severity accurately, which is shown in form of magnitude in damage feature values.



a)Damage Case 1 (30% reduction) b) Damage Case 2 (50% reduction)

Figure 8: K-S distantce of ARMAX residuals at random temperautres



a) Damage Case 1(30% reduction) b) Damage Case 2 (50% reduction)

Figure 9: Damage Features (after eliminating temperature effects)

4. CONCLUSION AND RECOMMENDATION

To compensate the environmental effects in damage detection process of real life structures, a new method based on ARMAX residual error with sensor clustering and artificial neural network was proposed for detecting damage under varying temperatures. A new damage feature is proposed by subtracting the influences due to temperature changes in the damage features from the ARMAX model, multiplied with the difference between squared healthy frequencies and squared damaged frequencies after correcting for temperature effects. The natural frequency component in the damage feature highlights the global changes in the system properties whereas the ARMX component highlights the localized effects. By doing so, the performances of the damage feature for assessing the existence and location of the damage is optimized. A numerical model of a three span bridge-type structure was created to verify the method proposed. Results showed that new damage features work well and stable at various temperatures.

Though capabilities of the proposed method are demonstrated for damage detection and localization under temperature effects by numerical simulations, experimental verifications are planned in near future. Furthermore, the method is being improved for ambient vibration analysis.

REFERENCES

Bernal, D., and Beck, J. (2004). Preface to the Special Issue on Phase I of the IASC-ASCE Structural Health Monitoring Benchmark. *Journal of Engineering Mechanics, 130*(1), 1-2.

El Bantli, F., and Hallin, M. (2001). Kolmogorov-Smirnov tests for AR models based on autoregression rank scores. *Lecture Notes-Monograph Series*, 111-124.

Fan, W., and Qiao, P. (2011). Vibration-based damage identification methods: a review and comparative study. *Structural Health Monitoring, 10*(1), 83-111.

Fanning, P., and Carden, E. (2001). *Auto-regression and statistical process control techniques applied to damage indication in telecommunication masts.* Paper presented at the Key Engineering Materials.

Gul, M., and Catbas, F. N. (2011). Structural health monitoring and damage assessment using a novel time series analysis methodology with sensor clustering. *Journal of Sound and Vibration, 330*(6), 1196-1210.

Hios, J., and Fassois, S. (2014). A global statistical model based approach for vibration response-only damage detection under various temperatures: A proof-of-concept study. *Mechanical Systems and Signal Processing, 49*(1), 77-94.

Khanukhov, K. M., Polyak, V., Avtandilyan, G., and Vizir, P. (1986). Dynamic elasticity modulus for low-carbon steel in the climatic temperature range. *Strength of Materials, 18*(7), 917-920.

Ko, J., and Ni, Y. (2005). Technology developments in structural health monitoring of large-scale bridges. *Engineering structures, 27*(12), 1715-1725.

Kostic, B. Z. A Framework for Vibration based Damage Detection of Bridges under Varying Temperature Effects using Artificial Neural Networks and Time Series Analysis.

Kromanis, R., and Kripakaran, P. (2014). Predicting thermal response of bridges using regression models derived from measurement histories. *Computers & Structures, 136*, 64-77.

Mattson, S. G., and Pandit, S. M. (2006). Statistical moments of autoregressive model residuals for damage localisation. *Mechanical Systems and Signal Processing, 20*(3), 627-645.

Mei, Q. *Investigation of Time Series Analysis Based Damage Detection Methodologies for Structural Health Monitoring.* (Ms.C. Thesis), University of Alberta. Available from University of Alberta Era database.

Moser, P., and Moaveni, B. (2011). Environmental effects on the identified natural frequencies of the Dowling Hall Footbridge. *Mechanical Systems and Signal Processing, 25*(7), 2336-2357.

Nair, K. K., Kiremidjian, A. S., and Law, K. H. (2006). Time series-based damage detection and localization algorithm with application to the ASCE benchmark structure. *Journal of Sound and Vibration, 291*(1), 349-368.

Omenzetter, P., and Brownjohn, J. M. W. (2006). Application of time series analysis for bridge monitoring. *Smart Materials and Structures*, *15*(1), 129.

Peeters, B., and De Roeck, G. (2001). One-year monitoring of the Z 24-Bridge: environmental effects versus damage events. *Earthquake engineering & structural dynamics*, *30*(2), 149-171.

Sohn, H., Worden, K., and Farrar, C. R. (2002). Statistical damage classification under changing environmental and operational conditions. *Journal of Intelligent Material Systems and Structures*, *13*(9), 561-574.

Wang, X., and Makis, V. (2009). Autoregressive model-based gear shaft fault diagnosis using the Kolmogorov–Smirnov test. *Journal of Sound and Vibration*, *327*(3), 413-423.

Zhou, G., and Yi, T. (2013). Thermal load in large-scale bridges: a state-of-the-art review. *International Journal of Distributed Sensor Networks, 2013*.

Zhou, H., Ni, Y., and Ko, J. (2010). Constructing input to neural networks for modeling temperature-caused modal variability: mean temperatures, effective temperatures, and principal components of temperatures. *Engineering Structures, 32*(6), 1747-1759.

Zhou, H., Ni, Y., and Ko, J. (2011). Eliminating temperature effect in vibration-based structural damage detection. *Journal of Engineering Mechanics, 137*(12), 785-796.