SMAR 2015 – Third Conference on Smart Monitoring,
Assessment and Rehabilitation of Civil Structures

SMAR 2015

Damage Detection under Varying Temperature Influence using Artificial Neural Networks and Time Series Analysis Methods

Branislav Kostic[1] and Mustafa Gül[2]

[1]University of Alberta, Edmonton, Canada
[2]University of Alberta, Edmonton, Canada

ABSTRACT: In this study, a time series analysis based method is employed in conjunction with artificial neural networks for damage detection under temperature effects. Numerical model of a footbridge is used for obtaining vibration data, which is then used to create different time series ARX models for different sensor clusters. The difference between the fit ratios of the ARX models from the baseline healthy case and damage case is used as damage indicating feature (DF_{ARX}), which can indicate the location and severity of the damage if no detrimental temperature effects are present. In order to compensate for temperature effects, artificial neural networks are then employed, where temperature measurements are used as the inputs to the neural network. Finally the outputs of the neural network (DF_{NN}), are used for determining final Damage Features (DF), which are then used for damage detection under temperature effects. It is shown that the proposed method can be used to compensate the effects of temperature variability.

1 INTRODUCTION

Damage detection is considered as one of the most important components of Structural Health Monitoring (SHM). One of the most important issues with continuous SHM is the environmental effects on the measurement data. Especially for civil infrastructure systems, such as bridges, environmental factors can produce bigger effects in the response of the structure than the damage itself, causing misleading results. Temperature is considered as one of the most common and influential environmental effect on bridges. In this study, a time series analysis ARX method is employed along with artificial neural networks for damage detection under temperature effects. Vibration output data is then used to create different time series ARX models (auto-regressive models with exogenous input) for different sensor clusters. The difference between the fit ratios of the ARX models from the baseline healthy case and damage case is used as damage indicating feature (DF_{ARX}), which can indicate the location and severity of the damage if no detrimental temperature effects are present. In order to compensate for temperature effects, artificial neural networks are then employed, where temperature measurements are used as the inputs to the neural network. Finally, Damage Features (DF_{NN}), which are the outputs of the neural network, are used for determining final Damage Features (DF) which are then used for damage detection under temperature effects.

2 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. Linear time series difference equation is shown in Eq. 1 (Ljung 1999), representing the relationship of the input, output and the error terms:

$$y(t) + a_1 y(t-1) + ... + a_{n_a} y(t-n_a) = b_1 u(t-1) + ... + b_{n_b} u(t-n_b) + e(t) + c_1 e(t-1) + ... + c_{n_c} e(t-n_c) \quad (1)$$

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 *ai*, *bi*, and *ci*, and the model orders are *na*, *nb*, and *nc*.

A reduced form of this expression is given in Eq. 2, and represents an ARMAX model (Auto-Regressive Moving Average model with eXogenous input):

$$A(q)y(t) = B(q)u(t) + C(q)e(t) \quad (2)$$

where *A(q)*, *B(q)* and *C(q)* are polynomials in the shift operator q^{-1}, given in Eq. 3:

$$\begin{aligned} A(q) &= 1 + a_1 q^{-1} + a_2 q^{-2} + ... + a_{na} q^{-na} \\ B(q) &= b_1 q^{-1} + b_2 q^{-2} + ... + a_{nb} q^{-nb} \\ C(q) &= 1 + c_1 q^{-1} + c_2 q^{-2} + ... + a_{nc} q^{-nc} \end{aligned} \quad (3)$$

A(q)y(t) represents an AutoRegression, *C(q)e(t)* is moving average of noise, and *B(q)u(t)* is an external input.

If we adjust the model order, we can define different time series models. Therefore, by setting nc equal to zero, we get the ARX model, which is used in this study:

$$A(q)y(t) = B(q)u(t) + e(t) \quad (4)$$

Gul and Catbas (2011) proposed methodology which uses free vibration output-only data, considering that defining input parameters *u(t)* in the form of input forces, is usually not practical for civil structures. The basis of this methodology is the equation of motion of N degrees of freedom (DOF) for linear dynamic system:

$$[M]\ddot{x}(t) + [C]\dot{x}(t) + [K]x(t) = f(t) \quad (5)$$

where [M] is the mass matrix, [C] is the damping matrix, and [K] is the stiffness matrix. If we consider only the first row of the Eq. 5, and rearrange it for the free vibration case, we get the following equation for the acceleration output of the 1st degree of freedom (DOF):

$$\ddot{x}_1 = -\frac{(m_{12}\ddot{x}_2 + ... + m_{1N}\ddot{x}_N) + (c_{11}\dot{x}_1 + ... + c_{1N}\dot{x}_N) + (k_{11}x_1 + ... + k_{1N}x_N)}{m_{11}} \quad (6)$$

Using this relation, we can get output of a reference DOF using the outputs of the neighboring DOFs. In the ARX model this means that we can create a model for predicting the output of any DOF, with using the system outputs as the input terms u(t) in Eq. 4. Therefore, different sensor clusters containing a reference channel and its neighbour channels are formed. Considering that this approach is using acceleration data only, one of the assumptions is that the model is inherently considering velocity and displacement to be dependent on the acceleration response.

3 ARTIFICIAL NEURAL NETWORKS

Artificial Neural Networks (ANNs) are computational networks, which are simulating human networks of neurons (Graupe 1997). Connections between the nodes in the neural network mimic synapses in the human brain. These connections have different strengths called weights, which are obtained by a process of adaption - learning, from a set of training patterns (Gurney 1997). Considering that the input and the output data is used for training, this type of training belongs to the supervised network type. Weights are adjusted in order to produce desired output data.

Neural network in this thesis was used for prediction of data. It consisted of one hidden layer with 10 nodes, and of one output layer with 16 nodes, which corresponds to the number of sensor channels on the bridge. Steps of the Levenberg-Marquardt (LM) backpropagation algorithm, which isused for this network, are presented:

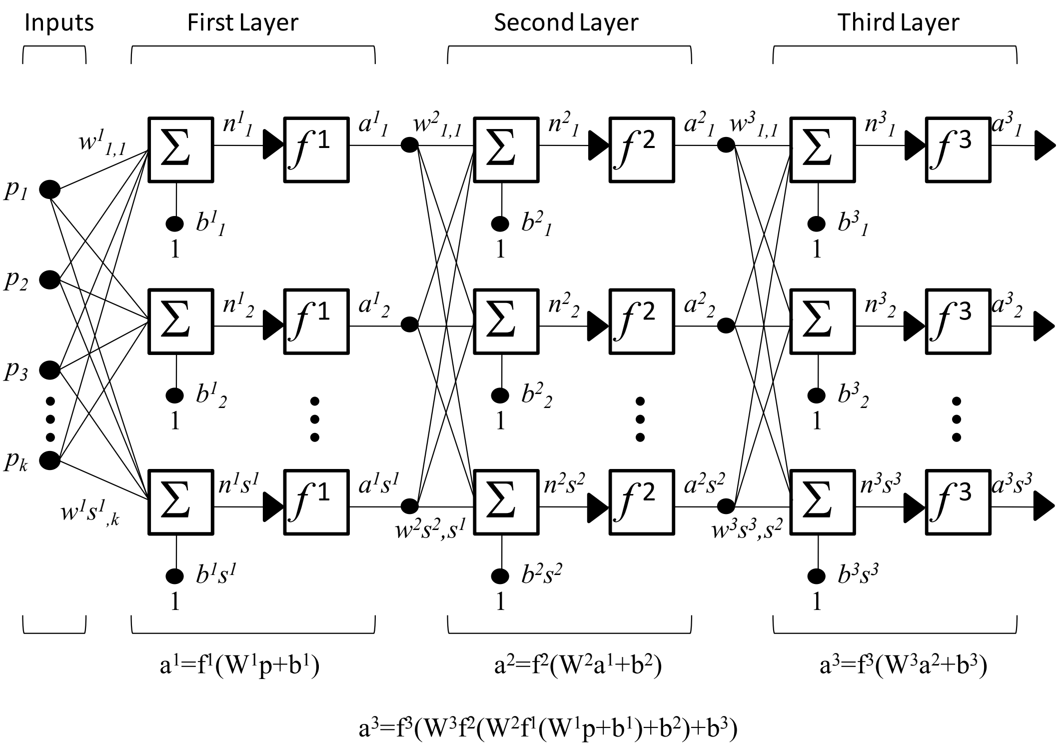

Figure 1. Multilayer Network Algorithm (adapted from Hagan et al 1996)

The net input to unit i in layer k + 1 is defined as (Hagan et al 1996):

$$n^{k+1}(i) = \sum_{j=1}^{Sk} w^{k+1}(i,j) a^{k}(j) + b^{k+1}(i) \qquad (7)$$

The output of unit i will then be:

$$a^{k+1}(i) = f^{k+1}\left(n^{k+1}(i)\right) \qquad (8)$$

where *w* are connection weights, and *b* are bias values.

In the Levenberg-Marquardt method, which is used in this thesis, performance index is used to minimize the sum of the squares of errors, with optimizing parameter vector β:

$$S(\beta)=\sum_{i=1}^{m}\left[y_i-f(x_i,\beta)\right]^2 \tag{9}$$

where y_i is measured vector, and $f(x_i)$ is estimated measurement vector.

At each step of this iterative process, δ (increment) that minimizes the following equation should be determined (Lourakis 2005):

$$\|y_i-f(x_i,\beta+\delta)\|\approx\|y_i-f(x_i,\beta)-J_i\delta\|=\|e-J_i\delta\| \tag{10}$$

This can be arranged as:

$$J^T J\delta=J^T e \tag{11}$$

Where J is a Jacobian matrix which contains first derivatives of the network errors with respect to weights and biases; $J^T J$ is the approximate Hessian matrix.

Levenberg also introduced the damping coefficient μ, which gives us the final form of Levenberg-Marquardt algorithm:

$$\delta=\left[\mu diag(J^T J)+J^T J\right]^{-1}J^T e \tag{12}$$

4 DAMAGE FEATURE

After obtaining the free vibration data of the footbridge from reference and neighbour nodes, damage analysis is conducted through determining the DFs for each reference point (Gul and Catbas 2011):

$$DF_{ARX}=\frac{FR_{Healthy}-FR_{Damaged}}{FR_{Healthy}}\times 100 \tag{13}$$

where the FR (Fit Ratio) is expressed with:

$$FR=(1-\frac{\|\{y\}-\{\hat{y}\}\|}{\|\{y\}-\{\bar{y}\}\|})\times 100 \tag{14}$$

where {y} is the measured output, $\{\hat{y}\}$ is the predicted output, $\{\bar{y}\}$ is the mean of {y} and $\|\{y\}-\{\hat{y}\}\|$ is the norm of $\{y\}-\{\hat{y}\}$.

Damage Features (DF_{ARX}) are then computed for numerical models of the footbridge with temperature load and introduced damage cases. Next step is to obtain the Damage Features (DF_{NN}) from the Neural Network, which represent output data of that network. Final Damage features are then defined as:

$$DF=abs(DF_{ARX}-DF_{NN}) \tag{15}$$

5 NUMERICAL VERIFICATION

The numerical model of a typical footbridge has been used for this study. It has two spans (2 x 22.05m), with 16 sensor channels located at the edge beams, at concrete deck level (Fig. 3). It consists of 4.1m wide and 19cm thick concrete deck, supported on HS 152x102x6 transverse and longitudinal girders. Transverse girders are located at 2.45m from each other. Vertical steel frame girders have the same cross section properties as girders at deck level, where top steel girders are located at 1.8m from the bottom steel girders.

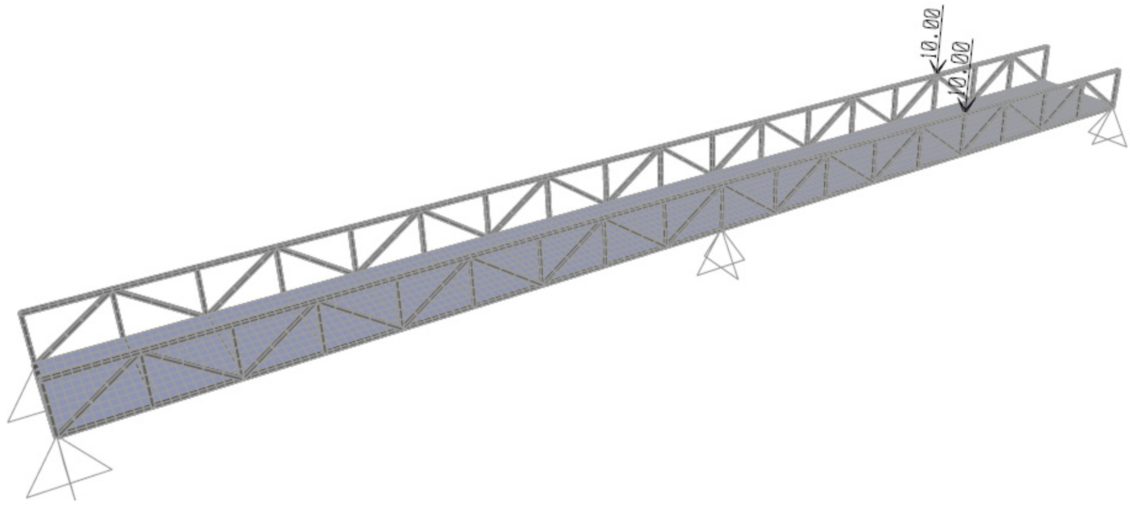

Figure 2. Numerical SAP2000 model of the Footbridge

Considering that there were 16 reference channels, 16 different sensor clusters were formed. Groups of sensor clusters are symmetric, with the only difference in reference channel. Therefore only first 8 sensor clusters with their corresponding reference and neighbour channels are given in Table 1.

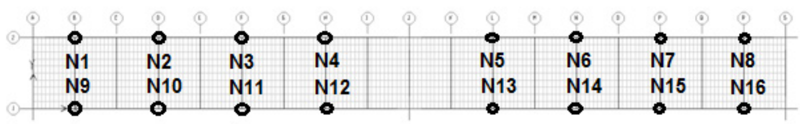

Figure 3. Sensor Arrangement

Table 1. Sensor Clusters

Sensor Cluster	Reference Channel	Neighbor Channels
1	N1	N1, N2, N9, N10
2	N2	N1, N2, N3, N9, N10, N11
3	N3	N2, N3, N4, N10, N11, N12
4	N4	N3, N4, N5, N11, N12, N13
5	N5	N4, N5, N6, N12, N13, N14
6	N6	N5, N6, N7, N13, N14, N15
7	N7	N6, N7, N8, N14, N15, N16
8	N8	N7, N8, N15, N16

5.1 Damage Cases

Damage cases which include reduction and increase of stiffness were chosen to represent some of the typical damages that can occur at a footbridge structures. In damage case 1 reduction of stiffness was simulated as a reduction of steel material modulus of 10% for all elements between channels 2&3 and 10&11. For real type structures this reduction can occur if there is a reduction in cross section of elements. Case 2 introduces fixed support instead of a pinned support at channel 16 location. This damage case introduces increase of stiffness in the model.

5.2 Analysis Method

Two rectangular pulse forces of 0.3 sec duration and 10kN amplitude, were used for exciting the structure at the top steel beam level – one at channel 7 location, and the other between channels 14 & 15 (Figure 2). It should be noted that the methodology is also applicable to ambient vibration data where different techniques can be used a pseudo-free response data. In order to provide free vibration data for the ARX model, the starting point of the window used in the analysis was shifted 6 seconds from the force impact moment. Effect of the noise on Damage Features was not considered in this analysis, but will take part in the future segments of this research.

Based on the iterative process of determining the optimal value for the ARX model order nb in Eq. 1, a model order of nb=8 was adopted as the optimal one. Temperature variation was applied in two ways. Elastic material modulus was defined based on the temperature of bridge elements. Temperature load was also applied uniformly across the cross section of the elements, based on the temperature at the time of construction (default condition) and the current temperature.

Neural Network was trained with 500 input sets of data with 3 different temperature values. These temperatures represented environmental temperature values of three groups of bridge elements: top steel beams, bottom steel beams and concrete deck. Temperatures of these groups of elements were all related to the environmental temperature, which took a random value between -25°C and 55°C. Randomness of the temperature values was improved with introducing random value of ±2.5°C for temperature of each group. Corresponding output data comprised 500 sets of damage features values (DF_{ARX}) for the 16 channels located on the sides of the bridge deck. These damage features were obtained from numerical models with temperature effects only, and no damage cases. Three baseline cases were used for this analysis, with two cases at extreme negative and positive temperatures, and one in the middle of the temperature range. Damage Features from all three baseline cases were analyzed, and the envelope of all the Damage Features was adopted at the end.

5.3 Analysis of the Results – DC1& DC2

As a first step of the analysis, Damage Features (DF_{ARX}) for damage case without temperature effect were calculated, where damage is clearly indicated (Fig. 4). These values of the Damage Features should correspond to the final Damage Features (*DF*) for damage case with the temperature effect. In Fig. 5 Damage Features for damage case with random temperature effect are shown. We can see that for most of the random temperatures damage is not clearly indicated. Fig. 6 is showing $DF_{NN,}$ which are output data values from the Neural Network, for the input data containing temperature values of the models with damage cases and the temperature effect. In the Fig. 7 final Damage Features (*DF*) are indicated, which are corresponding to the values indicated in Fig. 4. This proves that the temperature effects on Damage Features were successfully compensated for this damage case.

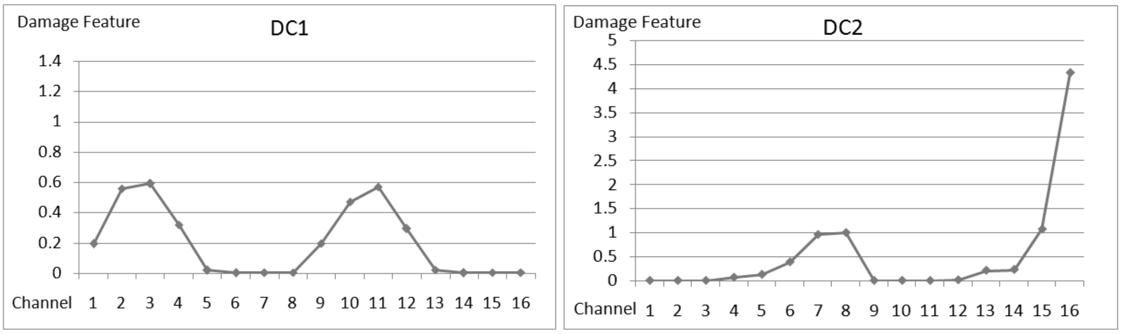

Figure 4. Damage Features for damage case only (DF_{ARX}) – DC1 (left), DC2 (right)

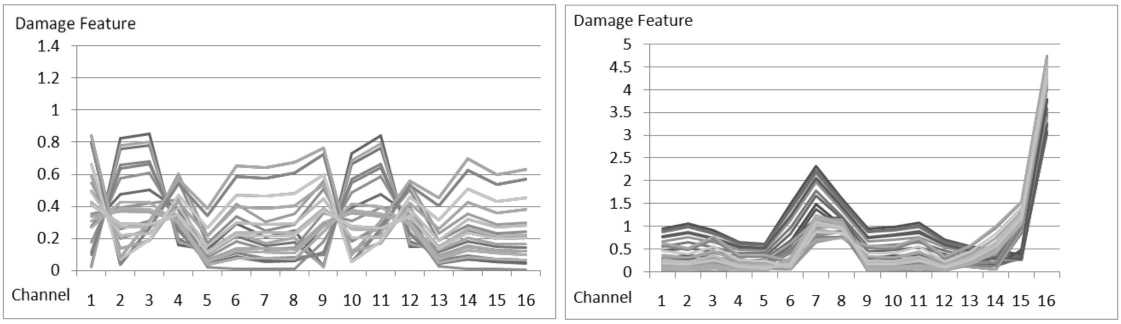

Figure 5.DF_{ARX} of damage case with temperature, first 10 random temperatures – DC1 (left), DC2 (right)

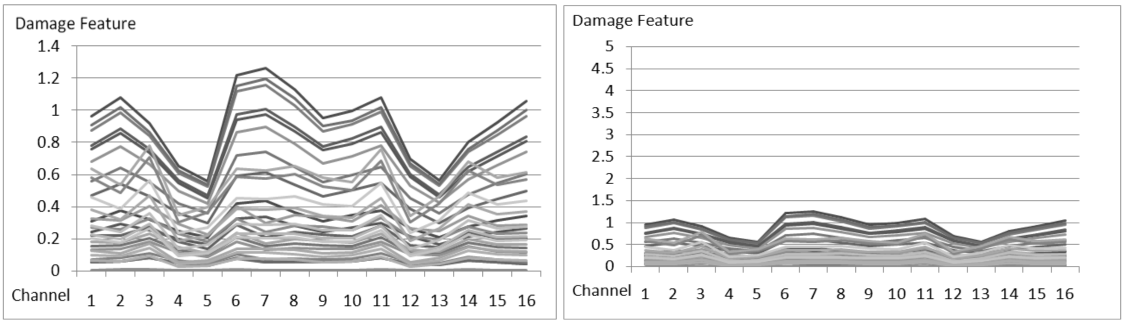

Figure 6.DF_{NN} for temperature only effect, first 10 random temperatures – DC1 (left), DC2 (right)

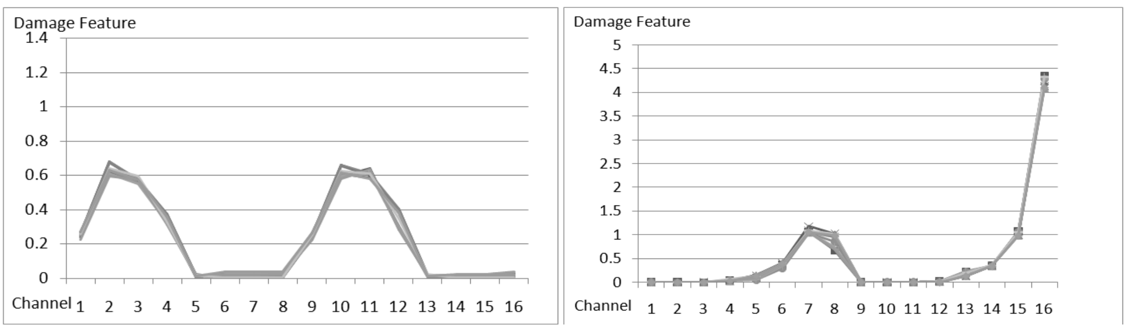

Figure 7.*DF* for damage cases with temperature, first 10 random temperatures – DC1 (left), DC2 (right)

Same steps were conducted for DC2 as with the DC1. In Fig. 4 the highest DFs are at the channel 16, which shows the exact location of the damage. In Fig. 5 we can that damage features for this damage case are higher than in DC1, therefore temperature effects do not affect DFs from this damage at the same level as in DC1. However, DC2 involves change of support stiffness, which is different type of damage than in DC1. Also, DC1 causes reduction of the stiffness in the structure, while in DC2 we have increase of the support stiffness. Therefore, DFs in Fig. 7 prove that this method can successfully compensate temperature effects for damage cases of stiffness increase and decrease, which is important for proving robustness of this method.

6 CONCLUSION

Time series analysis based method is employed in conjunction with artificial neural networks for damage detection of numerical footbridge model under temperature effects. Purpose of this method is to compensate detrimental temperature effects on this damage detection method. Numerical model of a typical footbridge was analyzed in this procedure. Based on the results for 2 typical damage cases, it can be concluded that his approach gives satisfactory results for detection, localization, and estimation of the structural damage in this model, even with variable temperature load. In order to verify further robustness of this method, experimental laboratory model as well as full-scale structure should be analyzed with ambient vibration data.

7 REFERENCES

CAN/CSA-S6-06, Canadian Highway Bridge Design Code 2006

Demuth, H. and Beale, M. 2002 *Neural Network Toolbox - For Use with MATLAB* MathWorks

Graupe, D. 1997. *Principles of Artificial Neural Networks*, Advanced Series on Circuits and Systems – Vol. 3, World Scientific

Gul, M. and F. N. Catbas 2011. *Structural Health Monitoring and Damage Assessment using a Novel Time Series Analysis Methodology with Sensor Clustering*. Journal of Sound and Vibration , 330(6): pp. 1196-1210.

Gurney, K. 1997. *An Introduction to Neural Networks*, UCL Press

Hagan, M.T. and Demuth, H.B. 1996 *Neural Network Design* PWS Publishing Company

Khanukhov, K.M., Polyak, V.S., Avtandilyan, G.I. and Vizir, P.L. 1986 *Dynamic elasticity modulus for low-carbon steel in the climactic temperature range* Central Scientific-Research Institute of designing steel structures, Moscow, translated from Problemy Prochnosti 7 55–58.

Kostić, B. and Gül, M. 2014 *Damage assessment of a Laboratory Bridge model using time series analysis* 9th International Conference on Short and Medium Span Bridges, Calgary, Alberta, Canada

Ljung, L. 1999. *System Identification: Theory for the User*, Upper Saddle River, NJ, Prentice-Hall.

Lourakis, M. 2005. *A Brief Description of the Levenberg – Marquardt Algorithm Implemented by levmar*, Foundation for Research and Technology – Hellas

Moser, P. and Moaveni, B. 2011 *Environmental effects on the identified natural frequencies of the Dowling Hall Footbridge* Mechanical Systems and Signal Processing, vol. 25, no. 7, pp. 2336–2357.

Sabeur, H., Colina, H. and Bejjani, M. 2007 *Elastic strain, Young's modulus variation during uniform heating of concrete* Magazine of Concrete Research, 59 (8) 559–566.