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FOOTBRIDGE MODEL UPDATING BASED ON MODAL DATA USING SENSITIVITY METHOD AND PARTICLE SWARM OPTIMIZATION

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Abstract. *Model updating is an important design task when dealing with numerical models that are confronted to experimental data. In this paper, an investigation is carried out in order to update a footbridge finite element numerical model using the Sensitivity Method and Particle Swarm Optimization. The analyzed footbridge has 34.08 m in length, 2.4 m in width and 2.25 m in height. Modal parameters are obtained by the solution of the corresponding eigenvalue-eigenvector problem and numerical simulations with the updated model are performed in the time domain. The numerical model results are compared to experimental measurements in the actual footbridge and used as metric for the updating. The Young´s modulus, material density of the metallic components and corresponding concentrated masses were elected as the parameters to be updated due to uncertainty in their evaluation. The baseline values for the Young´s modulus parameter and material density were 210.00 GPa and 7850 kg/m³ (structural steel), respectively, which were updated to 184.36 GPa and 7883.45 kg/m³ using the Particle Swarm Optimization. For the Sensitivity Method these values were 200.00 GPa and 7782.34 kg/m³. The corresponding natural frequencies presented errors lower than 2.75% for the first seven natural frequencies. The resulted numerical natural frequencies were fairly close to the experimental ones and confirmed the adequacy of the model to represent the main dynamic features of the footbridge.*

Keywords: *Model updating, footbridge, natural frequencies.*

1. INTRODUCTION

A structure may undergo changes in their dynamic behavior when subjected to loads. Several cases of excessive vibration on footbridges due to human-induced loads have been reported, being usually related to crowd condition (Barker and Mackenzie, 2008; Kim, *et al*., 2008). These situations occur because some footbridges have natural frequencies that are very close to the dominant frequencies of the pedestrian induced load and therefore they have a potential to undergo excessive vibrations. Several studies are applied to evaluate the cases of high structural amplitudes, where the pedestrian structure interaction can compromise the strength capacity of the footbridge (collapse, fatigue) as well as in small amplitudes, where this affects the serviceability and perception, since humans are quite sensitive vibration receivers. As stated by Griffin (2004) the human body is a complex mechanical system with inherent mass, stiffness and damping properties. As such, there is a large inter-subject variability in the vibration felt by different people. Furthermore, the same person is likely to react differently to the same vibration, causing a considerable intra-subject variability in the dynamic response to vibration.

In relation to design aspects, Zuo *et al*., (2012) affirms that engineering projects such as footbridges sometimes have large spans. As a result, these structures have lower natural frequencies. It is observed that these structures do not present a suitable project, generating large amplitudes of vibration when subjected to pedestrians loading, becoming the dynamic response very sensitive to even small variations in modal properties, such as damping ratio, natural frequency and modal mass. The researchers pointed that the susceptibility of the footbridge to pedestrian excitation is due to synchronization of pedestrian footfalls with the footbridge vibration. The results also suggested that the pedestrians walking on the structure have an effect of added mass that may affect the vibration response of the footbridge. In this context, Alam and Amin (2010) also argue that in the last few years, the trend in footbridge design has been changed towards larger spans, slender structures with less weight. As a result of these design trends, many footbridges have become more susceptible to vibrations when subjected to dynamic loads, having an increasing of flexibility in dynamic behaviour. As a consequence, the stiffness and mass sometimes decrease, leading to smaller natural frequencies, becoming structures more sensitive to dynamic loads imposed by pedestrians or wind loads.

The aforementioned studies provided evidences that in structures subjected to a flow of pedestrians, for instance, footbridges in urban areas, a model updating should be considered in order to obtain numerical models more realistic. The main idea of the model updating is minimising the differences between the analytical and experimental models, so, this task can be treated as an optimisation problem being solved of different ways (for instance, using heuristic, deterministic and hybrid methods). According to Zivanovic *et al*., (2007) once the modal dynamic properties of a footbridge (mainly natural frequencies and mode shapes) are identified experimentally and the level of error introduced by the initially developed FE model is identified, their drawbacks in the modeling can be found and the initial FE model can be corrected. The model updating can be considered as an attempt to use the best features from both the experimental and analytical model. The process of updating can be used, for instance, to produce more reliable results in further dynamic analysis. Typically, the updating procedure minimises the differences between the finite element model and the modal properties experimentally estimated. This practice is done by changing some uncertain modelling parameters, which have the potential to influence modal properties of the structure.

Initially, the updating process consists of manual tuning of the parameters of interest. But this task is tedious, being necessary spend much time to get good results. So, an automatic model updating using some specific software or method is necessary. Zivanovic *et al*., (2007) affirms that the manual tuning involves changes of the model geometry and modelling parameters by trial and error, using engineering judgement. In this step, it is possible analyse the effect that each parameter may have on the dynamic behaviour of the entire system. The aim is to bring the numerical model closer to the experimental one. On the other hand, the automatic updating is faster and can update several variables simultaneously, taking into account a larger number of uncertain parameters. One of the difficulties found during the model updating is the choice of which parameters should be changed. During the modelling of a structure, it is generally expected that finite element models present uncertainties, such as stiffness of supports, effects of non-structural elements, clearances, material properties, uncertainties in the structural geometry, inaccurate representation of boundary conditions and inevitable differences between the properties of the designed and as-built structure, these uncertainties may influence in the results of an dynamic analysis. These factors increase the need of verification of finite element models of footbridges after their construction. So, the purpose of model updating is to improve the uncertain parameters and/or imprecise, obtaining a finite element model with closer representations of reality.

In this paper, an investigation is carried out in order to update a footbridge finite element numerical model. The paper presents a comparison of two optimization methods that are used to model updating: Sensitivity Method (SM) and the Particle Swarm Optimization (PSO). The results are compared in terms of accuracy of the updated frequencies. The analyzed footbridge has 34.08 m in length, 2.4 m in width and 2.25 m in height. The structure is modelled as a space truss. Transient solutions are obtained using the Newmark method. The results of the numerical model (frequencies and vibration modes) are compared with the experimental measurements. The experimentally identified modal properties were previously obtained by Brasiliano *et al*., (2008). A MATLAB finite element program, is used to predict footbridge dynamic characteristics, such as natural frequencies and mode shapes.

2. ANALYZED FOOTBRIDGE

The analyzed structure is a composite footbridge. This structure is located in the city of Brasilia, Brazil and provides a link between commercial areas, crossing a heavily trafficked road. The footbridge has 34.08 m in length, 2.4 m in width and 2.25 m in height. Figure 1 shows a lateral view of the footbridge. The principal dimensions of the metallic components of the footbridge are show in Fig. 2. All the connections between metallic components of the structure were done by welding.

Figure 1. Lateral view of the analyzed footbridge.

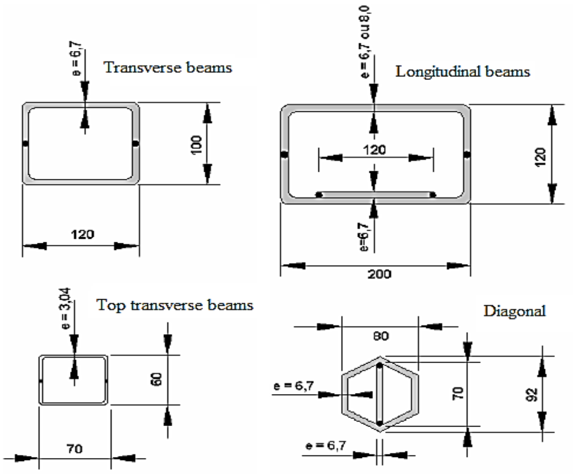


Figure 2. Metallic components of the structure (unit: mm). (Brasiliano *et al*., 2008).

Regarding to other components, according to Brasiliano *et al*., (2008) the footbridge roof was constructed with reinforced mortal arch planks with 2.84 m in length and 2.4 m in width. The arch planks had a radius of 1.74 m and a thickness of 0.02 m. The roof planks are supported by the longitudinal top beams along all their length. The deck floor consisted of reinforced concrete planks with 0.4 m in width, 2.84 m in length and 0.03 m in thickness. The handrails consisted of hollow tubular steel bars (top bar had a diameter of 63.5 mm and a thickness of 1.6 mm; secondary bars had a diameter of 38.1 mm and a thickness of 1.6 mm). These components are linked to the main structural trusses. Additional information regarding design details of the components, materials properties, etc. can be found in Brasiliano *et al*., (2008).

2.1 Experimental measurement

A detailed description of the experimental tests was presented by Brasiliano *et al*., (2008). Herein, a brief explanation for the sake of clarity is presented. The researchers used two methods to identify the footbridge dynamic properties (time domain methods): SSI-COV/ref and SSI-DATA/ref. These methods were applied to the acceleration records acquired (it was used a 32 channel Lynx data acquisition system). During the experimental tests, accelerometers were placed at several points on the footbridge to measure the vibration response. It was used nine piezoelectric accelerometers (sensitivity of 0.16 mV/g and 103.8 mV/g). The sampling frequency was 200 Hz. The signals were acquired during 15 seconds. The analyzed structure was excited by two pedestrians that walked naturally along of the footbridge. More details for the testing, placement of accelerometers and signal conditioner can be found in Brasiliano *et al*., (2008). Table 1 presents the first 7 measured natural frequencies and a description of the corresponding assumed mode shapes of the analyzed footbridge based on experimental and numerical data.

Table 1. Frequencies and mode shapes: experimental results, Brasiliano *et al*., (2008).

Experimental measurements		
Mode Number	Frequency (Hz)	Mode shape description
1	3.120	1st Lateral mode
2	3.920	1st Vertical mode
3	5.180	2nd Lateral mode
4	-	Not measured
5	8.230	1st Torsional mode
6	10.095	2nd Vertical mode
7	11.350	2nd Torsional mode

3. MODEL UPDATING

The experimental values of the natural frequencies of the footbridge were taken as reference values in order to update the numerical model. The baseline values for the Young´s modulus parameter and material density were 210.00 GPa and 7850 kg/m³ (structural steel) respectively. The natural frequencies obtained by the initial FEM (Finite Element Model) of the footbridge presented significant differences from the experimental results corresponding to the first six mode shapes of the analyzed footbridge (see Table 2). These differences come from some uncertainties in the structural geometry, material properties, boundary conditions etc. For these reasons, the finite element model of the footbridge must be updated. The model was updating according to the experimental results. The first six measured modes of vibration were targeted in the updating process. A constraint to the updating procedure was the introduction of an upper and lower limit for the analysed parameters (considering allowable values). For every mode of vibration, the error of the evaluated natural frequency was compared with the experimental value, defined as an absolute value of the relative difference (R) between numerical f_a and experimental f_e natural frequency, according to Eq. (1):

$$\mathrm{R} = \left|\frac{f_a - f_e}{f_e}\right| \tag{1}$$

The Young´s modulus, the material density of the metallic components and corresponding concentrated masses were elected as the parameters to be updated due to uncertainty in their evaluation. In the following, it will be presented two structural optimization techniques used in the model updating: Sensitivity Method (SM) and Particle Swarm Optimization (PSO).

3.1 Sensitivity Method (SM)

Sensitivity Method (SM) is a technique used for model updating that is based on gradients of the differences of the measured and predicted responses; this iterative optimization method updates the uncertain parameters in order to minimize the cost function error. Mottershead *et al*., (2011) states that this method is based upon linearization of the normally non-linear relationship between measurable outputs, for instance natural frequencies, mode shapes and the parameters of the model that needs to be updated. In this method, the variable $\boldsymbol{\theta}$ is the vector of unknown parameters $\boldsymbol{\theta} = (\theta_1, \theta_1, \ldots, \theta_{np})^T$ with dimension equal to the number of unknown parameters (*np*). The vector of the measured output parameters is represented by $\boldsymbol{z}^m = (z_1^m, z_2^m, \ldots, z_{no}^m)^T$, with dimension equal to the number of the measured output parameters (*no*) and $\boldsymbol{z}^p = (z_1^p, z_2^p, \ldots, z_{no}^p)^T = f(\boldsymbol{x}^m, \boldsymbol{\theta})\boldsymbol{z}^p$ is the vector of the predicted output parameters. The residual (difference between predicted and measured outputs) is defined at the *ith* iteration using the Eq. (2):

$$\delta\boldsymbol{z} = \boldsymbol{z}^m - \boldsymbol{z}^p \tag{2}$$

This equation holds to all realisations of the measured output parameters (*ns*). Using the Eq. (2) and truncating its Taylor expansion up to a first order, leads to Eq. (3):

$$\boldsymbol{\theta} = \boldsymbol{\theta}_o + \left.\frac{\partial z}{\partial \boldsymbol{\theta}}\right|_{\theta_o} \partial\boldsymbol{\theta} \cong \boldsymbol{\theta}_o + \boldsymbol{S}\delta\boldsymbol{\theta} \text{ For small variations in } \boldsymbol{\theta}. \tag{3}$$

According to Zivanovic *et al*., (2007), in the formulation of the Sensitivity Method, the experimental responses are expressed as a function of analytical responses and a sensitivity matrix (**S**), given by Eq. (4):

$$\boldsymbol{S} = \begin{bmatrix} \dfrac{\partial \boldsymbol{z}_1}{\partial \boldsymbol{\theta}_1} & \cdots & \dfrac{\partial \boldsymbol{z}_1}{\partial \boldsymbol{\theta}_{np}} \\ \vdots & \ddots & \vdots \\ \dfrac{\partial \boldsymbol{z}_{n0}}{\partial \boldsymbol{\theta}_1} & \cdots & \dfrac{\partial \boldsymbol{z}_{no}}{\partial \boldsymbol{\theta}_{np}} \end{bmatrix} \tag{4}$$

In this context, the Eq. (3) can be written as an error function vector, according to Eq. (5):

$$\boldsymbol{\varepsilon} = \delta\boldsymbol{z} - \boldsymbol{S}\delta\boldsymbol{\theta} \tag{5}$$

To take into account ill-conditioned or under-determined linear system of equations, that is a problem central to finite element model updating (Ahmadian *et al*., 1998; Natke, 1991) one can minimize a cost function based on the squared errors (cases where it is difficult to obtain a convergent solution because of an ill-conditioned sensitivity matrix) added to a regularization term, according to Eq. (6):

$$J(\boldsymbol{\theta}) = \boldsymbol{\varepsilon}^T \boldsymbol{W}_\varepsilon \boldsymbol{\varepsilon} + \lambda^2 \delta\boldsymbol{\theta}^T \boldsymbol{W}_\theta \delta\boldsymbol{\theta} \tag{6}$$

Here, $\boldsymbol{W}_\varepsilon$ and $\boldsymbol{W}_\theta$ are suitable diagonal weighting matrices that take into account the relative accuracy of the error measurements and parameter estimates. In this case, λ is a regularization factor (that provides a balance between the measurement residual and the side constraint) chosen for the improvement of the ill-conditioning problem based on the L-curves. One can minimize the previous cost function (the minimization of this function will maximize the agreement between the experimental and analytical model) using a first order approximation and obtain the recurrent parameter update, as defined in Eq. (7):

$$\boldsymbol{\theta}_{j+1} = \boldsymbol{\theta}_j + \boldsymbol{S}_j^T (\boldsymbol{S}_j \boldsymbol{W}_{\varepsilon\varepsilon} \boldsymbol{S}_j^T + \lambda^2 \boldsymbol{W}_{\theta\theta})^{-1} \boldsymbol{S}_j^T \boldsymbol{W}_{\varepsilon\varepsilon} (\boldsymbol{z}^m - \boldsymbol{z}^p \boldsymbol{\theta}_j) \tag{7}$$

In this paper, the objective function minimizes the differences between numerical and experimental frequencies.

3.2 Particle swarm optimization (PSO)

Particle swarm optimization (PSO) is a population based stochastic optimization technique developed by Kennedy and Eberhart (1995), inspired by social behavior of bird flocking or fish schooling. One of the reasons to choose such algorithm is the ability to deal with objective functions that may not be well behaved with multiple local optima. PSO optimizes a problem by having a population of candidate solutions (particles; the set of particles is generally referred as ‘swarm’), and moving these particles around in the search-space according to simple mathematical formulae over the particle's position and velocity (these parameters guide the direction of search of each particle along of iterative process). Each particle represents a potential solution for the problem and the measure of this potentiality is its cost function. The particle's movement is influenced by its local best known position but, is also guided toward the best known positions in the search-space, which are updated as better positions are found by other particles. It is expected to move the swarm toward the best solutions. In a minimization problem, ‘best’ simply means the position of the particle ($\boldsymbol{x}i$) with the smallest objective value $f(\boldsymbol{x}_i)$. Members of a swarm communicate good positions to each other and adjust their own position and velocity based on this information of good neighborhood positions. Thus, related to each particle, there is a set of design variables ($\boldsymbol{x}_i$) and the respective velocities ($\boldsymbol{v}_i$) that represent the potential solution of the optimization problem. The basic swarm parameters position and velocity are updated during iterations by Eqs. (8) and (9):

$$v_{i,j}^{k+1} = \chi\left[\bar{\omega} v_i^{k+1} + \lambda_1 r_1\left(xlbest_{i,j}^k - x_{i,j}^k\right) + \lambda_2 r_2\left(xgbest_j^k - x_{i,j}^k\right)\right] \tag{8}$$

$$x_{i,j}^{k+1} = x_{i,j}^k + v_{i,j}^{k+1} \tag{9}$$

$$\chi = \frac{2}{\left|2 - (\lambda_1 + \lambda_2) - \sqrt{(\lambda_1 + \lambda_2)^2 - 4(\lambda_1 + \lambda_2)}\right|} \tag{10}$$

Where $\bar{\omega}$ is the velocity inertia weight (previously set between 0 and 1), $x_{i,j}{}^k$ is the current value k of the design variable j and particle i, $v_{i,j}{}^k$ is the updated velocity of design variable j and particle i, $xlbest_{i,j}{}^k$ is the best design variable j ever found by particle i (this term indicate the experience or knowledge individual of each particle), $xgbest_j{}^k$ is the best design variable j ever found by the swarm, r_1 and r_2 are uniform random numbers in the range [0,1], λ_1 means the cognitive component (particle self-confidence), λ_2 means the social component (swarm confidence). It is usually set $\lambda_1=\lambda_2=2.0$. Both constants indicate how each particle is directed towards good positions taking into account personal and global best information.

The role of the inertia weight $\bar{\omega}$ is important for the PSO convergence. It is employed in order to control the impact of previous velocities on the current particle velocity. A general rule of thumb indicates to set a large value initially to make the algorithm explore the search space and then gradually reduce it in order to get refined solutions. It is possible to make updates based on the coefficient of variation ($CV=\sigma/\mu$) of the swarm cost function according to $\bar{\omega}=0.4[1+\min(CV,0.6)]$. Taking the error functions defined previously (mean and covariance), this algorithm can be used to update the parameters for a given set of experimental data. The χ parameter is used to avoid divergence behavior in the algorithm, which was developed based on convergence assumptions, as indicate by Bergh and Engelbrecht (2006). In the implementation of the PSO algorithm, first the positions and velocities of the particles are randomly generated. Subsequently, the particles entering in loop of the algorithm responsible by updates, until it reaches the stopping criterion.

3.3 Numerical model of the analysed structure

The footbridge was modelled using the MATLAB software. The structure was modelled as a space truss. The time domain responses were obtained by numerical integration using the Newmark method (Bathe, 1996) and the corresponding eigenvalues and eigenvectors of the dynamic system evaluated by QZ algorithm with a preliminary balancing step. The deck floor and handrails were modelled as distributed masses in the bottom chord. The roof was assumed as distributed masses along the top nodes. The displacements in x, y and z directions were constrained at nodes 1, 2, 5, 6, 7, 8 and constrained at nodes 3, 4 at y and z directions for simple supported condition. Figure 3 shows the discretization of the numerical model. Adequate diagonal member were properly added to simulate the diaphragm effect of the deck and roof. As indicated by the following results and discussions, this very simple model showed sufficient to adequately simulate the main dynamic behaviours of the structure.

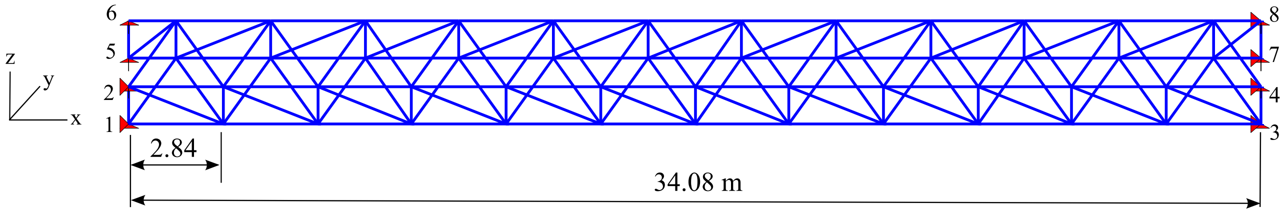


Figure 3. Space truss finite element model of the analysed footbridge.

3.4 Model updating results

The numerical model was updated to reproduce the dynamic features of the footbridge. The model updating results (frequencies and vibration modes) were compared with the experimental measurements obtained by Brasiliano *et al.*, (2008). Table 2 show frequencies values obtained from analytical and experimental modal analyses. These results corresponds to both methods used in the optimization: Particle Swarm Optimization (PSO) and Sensitivity Method (SM). It is also presented the initial FEM considering the nominal values.

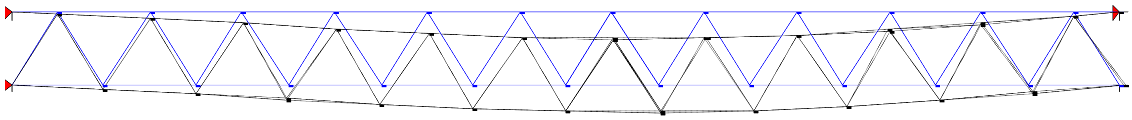
Table 2. First 7 updated natural frequencies and the corresponding differences to the experimental results.

Mode Number	Experimental Freq. (Hz)	Initial FEM Freq. (Hz)	Difference (%)	PSO Freq. (Hz)	Difference (%)	SM Freq. (Hz)	Difference (%)
1	3.120	2.758	11.603	3.034	2.756	3.064	1.795
2	3.920	4.736	20.816	3.920	0.000	3.918	0.051
3	5.180	5.827	12.490	5.279	1.911	5.309	2.490
4	-	6.669	-	6.207	-	6.290	-
5	8.230	8.541	3.779	8.230	0.000	8.321	1.106
6	10.095	10.505	4.061	10.122	0.267	10.261	1.644
7	11.350	12.302	8.388	11.238	0.987	11.362	0.106

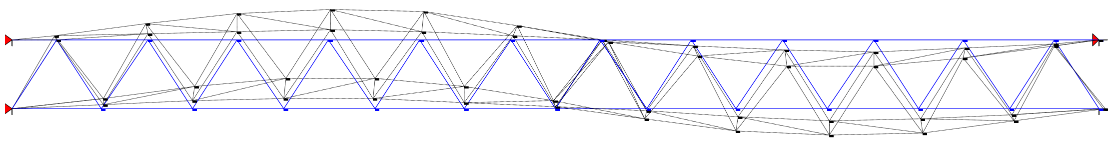
Note: Numerical mode shapes description (seven modes); 1st Lateral mode; 1st Vertical mode; 2nd Lateral mode with torsion; 1st Pure torsional mode; 2nd Lateral mode with movement of the deck; 2nd Vertical mode with torsion; 2nd Pure torsional mode.

The modal frequencies obtained from the initial FEM differ from the experimental ones by up to 20.82% and in average by 10.19%. Regarding to others results, after the model updating, consistency was observed when comparing the results for the two methodologies. Both structural optimization techniques (using Particle Swarm Optimization and Sensitivity Method) are in agreement with the measured results in the footbridge. The methodology that uses PSO is slightly better than the methodology using SM to update the modal frequencies of the footbridge. Considering the Particle Swarm Optimization, it can be seen that the differences between natural frequencies are reduced from 10.19% to 0.98% in average after the model updating. Concerning to the Sensitivity Method, the differences between natural frequencies are approximately 1.20% (mean values) after model updating, which are in the same order of magnitude of the PSO method. Regarding to the processing time, the Particle Swarm Optimization spent approximately 4 times the time spent by the Sensitivity Method. At 50 iterations, both analyses met steady state condition for the error norm. However PSO presented a lower converged error value than SM.

The updated parameters should be physically meaningful (cannot produce unrealistic parameter changes during the updating process) otherwise it will be very difficult to justify the results with respect to the actual structure. Considering the PSO method, after the model updating the Young´s modulus was reduced to 184.36 GPa while the material density increased to 7883.45 kg/m³. In the Sensitivity Method, the Young´s modulus and the material density were reduced to 200.00 GPa and 7782.34 kg/m³ respectively. Comparing experimental and numerical results in Table 2, one can note that the largest errors are related to the dynamic behavior to the footbridge in both lateral and torsional modes of vibration. Figure 4 depicts the first two numerical mode shapes for the vertical bending mode. This figure can be compared with experimental results obtained by Brasiliano *et al*., (2008) and shows good agreement.



(a)



(b)

Figure 4. Numerical mode shapes: a) 1st Vertical mode; b) 2nd Vertical mode with torsion.

Figure 4b shows that there is some influence of the torsional mode in the second vertical bending vibration mode. In this context, numerical results from Brasiliano *et al*., (2008) presents a combination of multiple mode shapes.

Once the finite element model has been updated, as future work, the next step of this study will be to carry out a dynamic analysis of the footbridge to evaluate the pedestrian-structure interaction. The pedestrians are expected to be treated as biodynamic models as proposed by Toso *et al*., 2013. Recently, a fully synchronized force model (FSFM) was presented by Toso and Gomes (2015) using this footbridge to assess the pedestrian-structure interaction.

4. CONCLUSIONS

In this paper, a finite element model updating and a comparison with experimental modal testing of a footbridge located in Brasilia, Brazil, was presented. The finite element model of the footbridge was developed using the

MATLAB program considering the design data, and modal parameters such as frequencies and mode shapes were determined. The first six modes shapes of the footbridge were identified via modal testing and published in previous work by Brasiliano *et al*., (2008). The initial analytical model and experimental dynamic characteristics of the modelled footbridge presented some non-acceptable differences when compared each other. The initial FEM revealed errors in the modal frequencies, particularly large for one mode (1^{st} vertical mode, difference of 20.82%). For other modes, the difference was less pronounced, being from 3.78% up to 12.49%. For this reason, the finite element model of the footbridge was updated to minimize the differences between analytically and experimentally estimated modal properties by changing some uncertain modeling parameters such as material properties and lumped masses. For model updating task it was investigated two optimization methodologies: Particle Swarm Optimization (PSO) and Sensitivity Method (SM). So, after the updating process, the maximum difference found in the natural frequencies were reduced from 20.82% to just 2.76%. The resulted numerically simulated frequencies were fairly close to the experimental ones and confirmed the adequacy of the updated model to represent main dynamic characteristics of the analyzed structure. Both used approaches produced results in close agreement with the experimental measurements, employing different optimization techniques to update the uncertain parameters. Regarding to numerical simulations, the Sensitivity Method has provided a quick convergence, although, this sometimes might represent local minima rather than a global minimum. Furthermore, a good initial guess of updating parameters is required. One of the advantages of Particle Swarm Optimization is that, unlike Sensitivity Method, no close initial guess is needed to achieve convergence to the global minimum. Besides, no gradients need to be calculated. Based on the analyzed example, it has been found that PSO presented better results in the model updating than SM.

5. ACKNOWLEDGEMENTS

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7. RESPONSIBILITY NOTICE

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