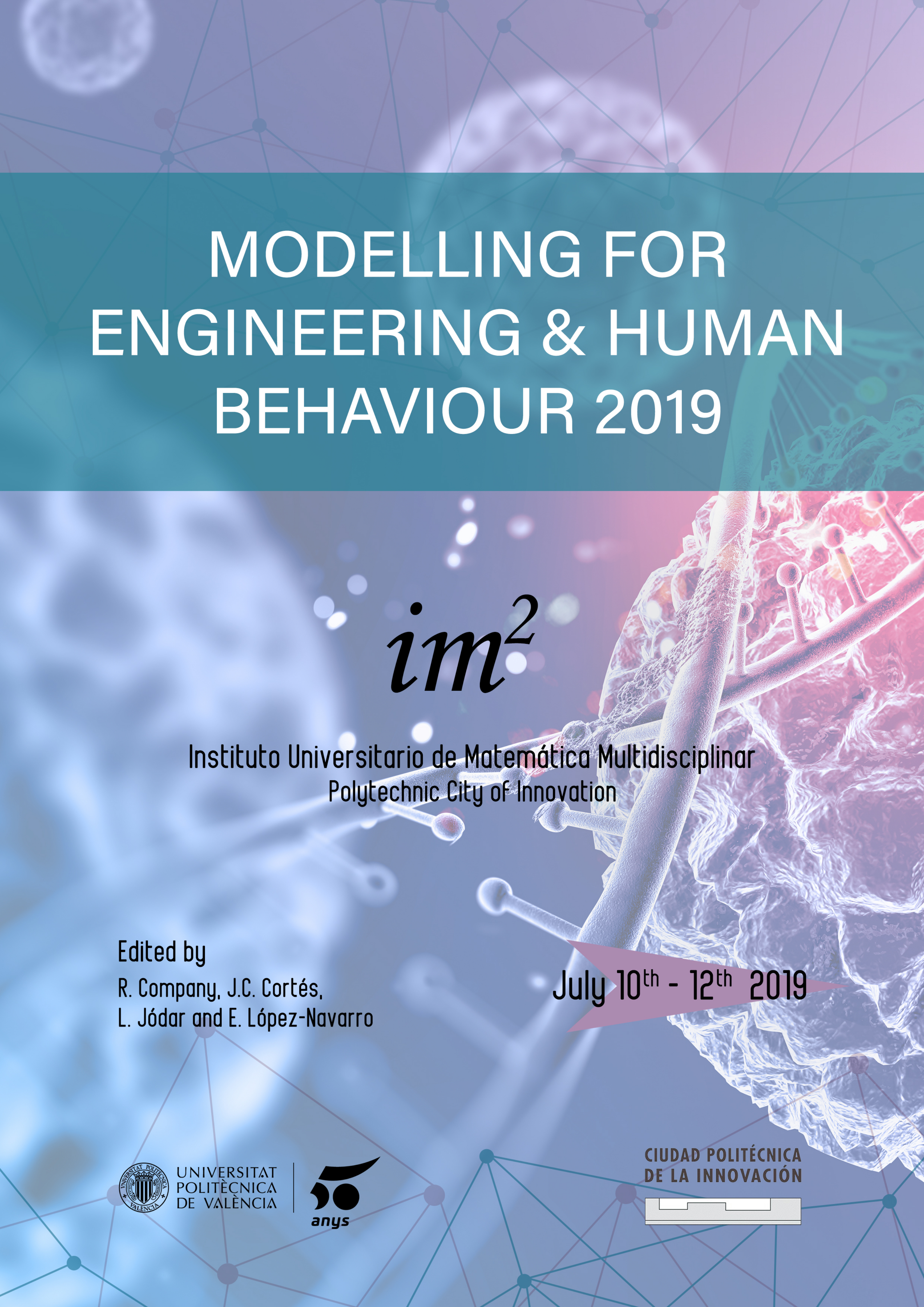

MODELLING FOR ENGINEERING & HUMAN BEHAVIOUR 2019

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Instituto Universitario de Matemática Multidisciplinar
Polytechnic City of Innovation

Edited by
R. Company, J.C. Cortés,
L. Jódar and E. López-Navarro

July 10th - 12th 2019

UNIVERSITAT POLITÈCNICA DE VALÈNCIA
50 anys

CIUDAD POLITÉCNICA DE LA INNOVACIÓN

Modelling for Engineering & Human Behaviour 2019

València, 10 – 12 July 2019

This book includes the extended abstracts of papers presented at XXIst Edition of the Mathematical Modelling Conference Series at the Institute for Multidisciplinary Mathematics “Mathematical Modelling in Engineering & Human Behaviour”.

I.S.B.N.: 978-84-09-16428-8
Version: 11/03/20
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Edited by: R. Company, J. C. Cortés, L. Jódar and E. López-Navarro.
Credits: The cover has been designed using images from kjpargeter/freepik.

This book has been supported by the European Union through the Operational Program of the [European Regional Development Fund (ERDF) / European Social Fund (ESF)] of the Valencian Community 2014-2020. [Record: GJIDI/2018/A/010].

Instituto Universitario de Matemática
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GENERALITAT VALENCIANA
Conselleria d'Hisenda i Model Econòmic

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A predictive method for bridge health monitoring under operational conditions

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1 Introduction

Approximately, the average number of bridge collapses per year is 1/4700 [1]. One of the most recent examples took place on August 14th 2018. The Morandi Bridge in Genoa collapsed killing 41 people and causing an economic damage that will take years to be repaired. Even Morandi Bridge was known to be in trouble long before collapse [2], experts affirmed that the collapse of the bridge was unexpected and sudden with respect to the monitoring that the bridge was subjected to [3]. In addition, common means and methods used for bridge health monitoring are intrusive and difficult the normal exploitation of the infrastructure – traffic deviations, incidences during maintenance operations, collisions, etc. -.

For this reason, a semi-empirical method based on strategical parameters and its measurement locations is exposed herein. In this method, the combination of numerical modelling with data registered in specific points of the structure allows to characterize the response of the structure under operational conditions in real time.

This strategy entails driving maintenance of fixed infrastructure assets from an observe and react approach failure towards a *predict and prevent* strategy [4].

2 Method

To achieve this goal, the purposed methodology is divided in following steps:

i) Numerical modelling. First of all, a **3D numerical representation of the structure** is carried out in a Finite Element Model software in accordance with 'as-built' information and maintenance history.

ii) Preliminary simulations. Instrumentation plan based on the identification of **critical parameters** depending on the structure typology, static and dynamic behaviour obtained

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from initial simulations performed on the 3D FEM model and **maximum response points**.

iii) Bridge instrumentation. Usual sensors required are: accelerometers for vibration analysis, strain gauges for stress / strain measurement, displacement sensors for relative movements, weather stations, cameras, inclinometers for element rotations and weather stations for thermal, humidity and wind intensity control.

iv) Calibration of the model. The static and dynamic response of the structure is adjusted by using load test data – static and dynamic tests' results – and measurements registered trough sensors installed.
Structural stiffness $[K_s]$ and boundary conditions are usually adjusted by using static load test results – deflections and displacements – while structural mass $[M]$ and support stiffness $[K_g]$ are fitted by a modal analysis and the dynamic load test results.

v) Structural damage simulations. Collapse and usability loss of the structure is determined by the simulation of several extreme loading scenarios. Results obtained in this stage allow to define admissible limits and tolerances to real time measured parameters.

vi) Prediction of the remaining lifespan and decision making assessment. By using degradation models – i.e. fatigue for metallic elements, rheological formulations for concrete, stiffness loss due to weather conditions – and real time measurements it is possible to obtain an updated prediction of the lifespan of the most relevant elements of the structure. The automation of this process combined with an alert system has strong potential for infrastructure managers.

In this paper, most relevant aspects about how steps i) to v) are applied to both bridges located in Chile is explained. And the step vi) is widely discussed.

Figure 1: Tolten bridge (left) and Seminario bridge (right).

3 Results

Steps i) and ii). A numerical 3D model with beam – for bar and truss modelling - and shell elements – for slabs and Tolten's embedded support walls – was carried out. Terrain was modelled as a set of springs $[K_g]$ attached to pier nodes. Self-weight plus dead loads were only considered from preliminary static and modal analysis.

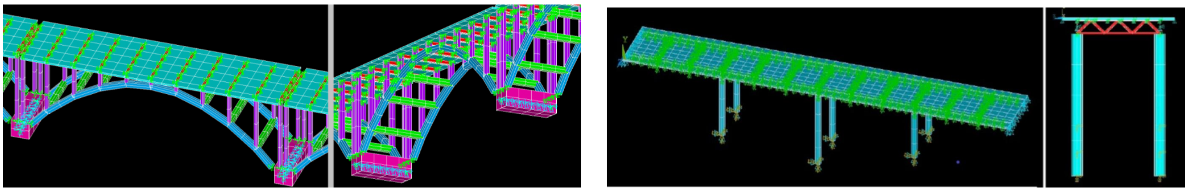

Figure 2: Tolten bridge numerical model (left) and Seminario bridge numerical model (right).

Step iii). By using accelerometers and inclinometers in intermediate span length points, inclinometers and scour sensors in piers and displacement sensors in joints it was possible to control the geometrical distortion of the structure in real time and under normal operation conditions.

Step iv). Static calibration was performed by locating a 20 ton truck in $\frac{1}{2}$ length of each span. Deflection deviation obtained after calibration between measured data and model prediction was lower than 5% in both bridges. Regarding dynamic calibration, it was carried out by achieving the first two vertical bending modes deviation did not exceed simultaneously a 0.5 Hz threshold. Accelerations registered with installed sensors were used for this purpose by applying Modal Operational Analysis technique. First two deck bending modes were used to calibrate the dynamic behaviour of the model in both structures. Results obtained, in terms of frequency deviation, after the calibration procedure were:

	Seminario Bridge		**Tolten Bridge**	
	1^{st} mode freq. $[Hz]$	2^{nd} mode freq. $[Hz]$	1^{st} mode freq. $[Hz]$	2^{nd} mode freq. $[Hz]$
Measured	4.458	5.223	1.728	10.096
Calculated	4.238	5.177	1.673	10.069
Deviation	0.220	0.046	0.055	0.027

Table 1: Results of dynamic calibration in both bridges using first two deck bending modes.

Step v). Ten load combinations were considered by taking into account maximum traffic in both lanes - Traffic 1 and Traffic 2 -, AASHTO lateral wind forces, maximum admissible scour and self-weight actions. Cross sectional failure of each structural element was considered as the limiting criteria. To characterize it, the following overstress ratio (OR%) is used:

$$\boldsymbol{OR}\% = \frac{\sigma_{vm}}{\sigma_{adm}}$$

where σ_{vm} and σ_{adm} are the maximum Von Mises stress obtained by the FEM analysis and the maximum strength of the corresponding material.

		Slab	**Pier**	**Beam**	**Truss**
		Current situation			
	OR%.	13,57%	8,13%	44,23%	43,79%
		No scour			
Traffic 1	**OR%.**	24,52%	12,33%	72,66%	70,23%
Traffic 2	**OR%.**	31,41%	16,24%	97,71%	99,31%
Wind	**OR%.**	15,27%	19,84%	47,19%	44,14%
Earthquake (long Axis)	**OR%.**	13,20%	63,84%	43,27%	77,50%
Earthquake (trans Axis)	**OR%.**	35,69%	49,93%	69,20%	39,46%

Slab	**Pier**	**Beam**	**Truss**
Max scour			
25,84%	12,57%	72,73%	70,28%
31,76%	16,38%	97,53%	99,46%
15,86%	21,81%	47,44%	44,15%
14,00%	69,26%	43,29%	84,85%
35,83%	93,78%	69,21%	46,93%

		Slab	**Pier**	**Diagonal tube**	**Trans Beam**	**Diag Beam**	**Girder**	**Truss**
		Current situation						
	OR%.	43%	12%	7%	18%	5%	22%	5%
		No scour						
Traffic 1	**OR%.**	105%	12%	7%	30%	5%	22%	5%
Traffic 2	**OR%.**	102%	30%	16%	44%	6%	59%	15%
Wind	**OR%.**	43%	12%	17%	18%	6%	23%	5%
Earthquake (long Axis)	**OR%.**	9%	89%	36%	7%	25%	8%	4%
Earthquake (trans Axis)	**OR%.**	60%	87%	46%	33%	8%	18%	9%
		Max scour						
Traffic 1	**OR%.**	104%	20%	11%	30%	5%	60%	10%
Traffic 2	**OR%.**	102%	30%	17%	44%	10%	59%	15%
Wind	**OR%.**	35%	12%	7%	16%	6%	21%	5%
Earthquake (long Axis)	**OR%.**	8%	81%	39%	5%	11%	8%	4%
Earthquake (trans Axis)	**OR%.**	50%	80%	44%	26%	19%	14%	9%

Table 2: Maximum Von Mises stress and OR% ratio obtained for Seminario bridge (above) and Tolten (below) simulations.

Step vi). Finally, the individual parameter evolution trends were obtained by minimizing deviation with measured data. This was carried out considering three months of continued hourly registers per each parameter. In addition, an Artificial Neural Network was also implemented. The objective of this ANN is to automate the detection of trend patterns in monitored parameters. From previous experiences, it is expected that this procedure, when becomes fully developed, allows to achieve less than a 9% of deviation in pathologies identification. For each bridge, following ANN parameters are defined:

	Seminario	**Tolten**
Inputs	**26** [Numerical results of 13 health parameters x 2 monitoring points]	**39** [Numerical results of 13 health parameters x 3 monitoring points]
Outputs	**36** [Potential pathologies]	**58** [Potential pathologies]
Training	**108** FEM simulations	**174** FEM simulations
Verification	>**2200** registers / health parameter	>**2200** registers / health parameter

Table 3: ANN parameters for Seminario bridge (left) and Tolten bridge (right).

4 Conclusions

In this paper, a non-intrusive method for continuous bridge health monitoring has been defined. In addition, an ANN has been implemented according with real field data measurements and numerical simulation results. Conclusions obtained are mentioned as follows:

- Combination of static and dynamic calibration allows to obtain high fidelity models. This procedure has been successfully applied to two different bridges in Chile: Tolten and Seminario.
- Seminario, which is a modern structure, shown a great performance in any analysed scenario. However, Tolten bridge, which was built in 1910's, shown its integrity damaged under severe seismic actions.
- Predictive techniques based on the study of individual evolution of each monitored parameter could not be adequate in structures with high variability in its registers. For this reason, AI techniques as ANN combined with real data collection and numerical modelling could improve substantially the assistance in infrastructure management in real time.

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