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Dynamic and static identification of base-isolated bridges using Genetic Algorithms

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ABSTRACT

In the paper, an identification approach based on a Genetic Algorithm (GA) is applied to the case study of a base-isolated, post-tensioned concrete bridge investigated in earlier contributions of literature. It is known that bearing isolators greatly influence the overall response of small- and medium-span bridges under dynamic loads, but in previous works it was seen that the characterisation of their elastic stiffness under small displacements may be inaccurate. In this work, based on in-situ test measurements obtained under static and dynamic loading conditions, inverse techniques based on GAs are successfully applied to the examined structural system, providing an efficient and well-calibrated structural identification of its main properties. Compared to other identification tools and classical correlation techniques, the main advantage deriving from the use of inverse approaches based on GAs typically manifests in the possibility to estimate a greater number of material parameters (e.g. properties of concrete as well as stiffness of the bearing isolators, etc.), and to critically assess the accuracy of the identification. Based on rather good correlation between test measurements and finite element (FE) model updating, it is expected that the same technique could be applied to various structural typologies and systems.

1. Introduction

The maintenance, safeguard and health monitoring of civil structures and bridges represent a topic of large interest for researchers, owners and users. Existing structures need to be assessed according the prescriptions of modern building codes; new constructions can benefit from the possibility of detecting any damage or loss of performance offered by continuous monitoring. In both cases, the analysis generally involves accurate numerical modelling of the structure, which must be calibrated according to the actual response (model updating) when it is excited by dynamic or static loads. A crucial step in the mechanical calibration of FE-models could derive, for example, from uncertainties on the actual boundary conditions, hence resulting in improper mechanical description of materials and inaccurate numerical investigations. This is the case of base-isolated structures, and specifically base-isolated bridges, where bearing-isolators are usually used to provide appropriate ultimate displacements under seismic events [1–5]. While the mechanical characterisation of these isolators under high-strain loads is typically provided by producers (e.g. [6]), however, it is well-known that "in-situ" static and dynamic tests carried out on bridge structures could induce in them maximum deformations markedly lower than their expected ultimate performances, hence resulting in difficult estimation and assessment of the effective in-plane horizontal stiffness provided by the isolation system. Structural identifications discussed in [7] for base-isolated bridges, for example, resulted in a satisfactory behaviour of the seismic isolators, but in identified bearing stiffnesses significantly higher than the reference experimental values. The lack of correlation between identified and experimental stiffness (and damping parameters) was justified in that case both by the application of low-strains only (e.g. magnified friction mechanisms and uncertainty in their estimation), and by the interference of non-structural components on the response of the whole structural systems or structural anomalies not taken into account during the design stage.

The calibration of material parameters and boundary conditions in numerical models can be performed by using the results from dynamic and static tests. The experimental modal analysis can be accomplished with three major testing procedures: ambient vibration [8], forced vibration [9] and free vibration [10]. A review of these three approaches may be found in [11]. Whichever testing procedure is used, some responses are measured and then used as input for the parameter calibration. Three basic types of data are used in dynamic identification: time domain, frequency domain

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and modal model. During experimental modal analysis, the sampled time-series data are processed into the frequency response function (FRF) data. These frequency data are then further processed by curve fitting to obtain the modal model, namely the natural frequencies, damping ratios and mode shapes. Data from each of these steps may be used in the identification: see for example [12] (time-domain data), [13] (FRF data) and [14] (modal data). Static tests have comparatively less variety in the post-processing, since the measured responses are directly used in the calibration [15].

The identification process is carried out by inverting the forward operator, which links some parameters of the numerical model to the measured response. Since the explicit analytical inversion is not always possible, the solution is usually attained by solving an optimisation problem in which a discrepancy between experimental and computed data is minimised. In the literature, this approach is widely used in the field of deterministic inverse problems: differences exist in the formulation of the discrepancy (or cost) function to be minimised [16] and in the minimisation algorithm.

In this work, an approach for the characterisation of the main model parameters of an existing post-tensioned concrete, base-isolated bridge, based on the minimisation of a discrepancy function by means of a Genetic Algorithm (GA), is proposed. It makes use of the experimental data from the static tests and the dynamic properties (frequencies and modes) extracted via experimental modal analysis previously described in [17]. It is shown how different sources of information may be embedded within the same procedure for both dynamic and static identification. Unlike [17], where a simplified analytical procedure was proposed in order to estimate the stiffness of the isolators, here the set of unknown parameters is enlarged as to include Young modulus of the concrete constituting piers and deck, and the identifiability of all parameters is assessed by studying the relationship between the discrepancy function value and each parameter. Different formulations for the dynamic discrepancy function are proposed and critically discussed, and the differences in the results reasonably explained.

2. The identification process

Let us be given a physical system and a mathematical model describing it. The identification process consists of finding some parameters (constitutive parameters, boundary conditions, etc.) $\boldsymbol{p}$ of the mathematical model that give a “computed” response as close as possible to the experimental one. The “closeness” is made explicit by the definition of a discrepancy (or cost) function which measures the discrepancy between the two responses. Thus, the problem can be seen as an optimisation problem, in which the discrepancy function must be minimised in the process.

Some aspects are worth to be pointed out:

– The mathematical (numerical or analytical) model must be as representative as possible of the real behaviour of the structure. Any important feature affecting the response must be properly represented: anisotropy, nonlinear behaviour, boundary conditions, position and magnitude of masses, etc. A usual choice in engineering identification problems is to model the structure using a finite element (FE) discretization.
– The experimental setup must significantly involve the sought parameters, i.e. the sensitivity of the response to the variation of the parameters must be sufficiently high.
– All experimental data are affected by errors, and this must be accounted for in the definition of the response to be measured, in their post-processing (if needed) and in the accuracy of the results of the identification process.
– The analytical form of the discrepancy function $\omega(\boldsymbol{p})$ must take into account different precision of instrumentation when different types of measured variables are considered (loads, displacements, strains, frequencies, etc.). In the simplest form, it reads:

$$\omega(\boldsymbol{p}) = \boldsymbol{R}^T \boldsymbol{W} \boldsymbol{R} \tag{1}$$

with $\boldsymbol{R} = \boldsymbol{y}^c(\boldsymbol{p}) - \boldsymbol{y}^m$ being the residual vector between some measured variables y_i^m, with $i = 1, \ldots, N$ (N number of measurements) and the computed counterparts y_i^c, that are obtained for a chosen set of trial parameters $\boldsymbol{p}$. $\boldsymbol{W}$ is a weight matrix that accounts for the correlation between response variables and the measurement scattering.
– Finally, the optimisation algorithm influences the accuracy of the results since, according the well-known “no free lunch theorem” [18], no algorithm is suitable for all problems. The presence of local optima, discontinuities in the function or in its derivatives can make the problem not solvable for some of them.

Each of these points will be exploited in this work. In particular, the optimisation algorithm is described in Section 3; the experimental setup and the FE model describing the structure are described in Sections 4.1 and 4.2, and a discussion about the sensitivity of the response on the sought parameters, the use of different discrepancy functions, the role of errors in the recorded data is presented together with the numerical application in Section 4.3.

3. The Genetic Algorithm

In order to solve the identification problem by minimising Eq. (1), a numerical iterative procedure must be used. To this aim, some of the most widely used approaches are gradient-based methods, such as Line Search [19] or Trust Region [20], which solve the problem by finding a stationary point of the discrepancy function. This strategy involves the computation of the Jacobian matrix of a solution candidate at each iteration and updating the point in the iterative process. Although computationally appealing, since the number of forward evaluations is generally rather low, these methods are local in scope, and can fail when the continuity and even the convexity of the cost function are not strictly satisfied in the search space. In this respect, global methods as Genetic Algorithms [21] are more general and they have been effectively employed in identification problems in previous research [22–25]. In addition to overcoming the mentioned drawbacks of gradient-based methods (by escaping local optima and not making use of derivatives), in this paper it will be shown that, in the GA framework, it is possible to qualitatively assess the identifiability of a parameter by studying the convergence process and the parameter–discrepancy function plots.

The main idea of this well-known approach is to let a *population* of several candidate solutions (*individuals*) evolve in the search of the optimum, throughout a certain number of *generations*. Compared to gradient-based algorithms, in which a single solution is updated in the search for the optimum, the use of populations of candidate solutions completely changes the perspective of the optimisation process. Clearly, the computational effort is usually higher in the GA approach, since one iteration consists of the evaluation of the discrepancy function for each individual in the population instead of a single candidate. On the other hand, the convergence may be seen as a process in which the population reduces its size in the parameter and fitness spaces, being distributed in the last generation around the best individuals [26]. The converged population distribution, thus, carries some information about the well-posedness of the problem, the number