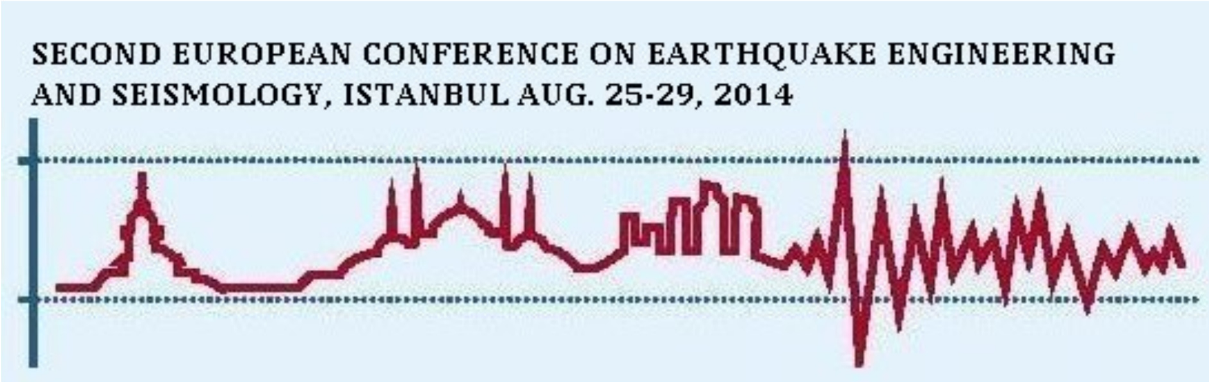

DEVELOPING FRAGILITY FUNCTIONS FOR ROADWAY BRIDGES USING SYSTEM RELIABILITY AND SUPPORT VECTOR MACHINES

Pierre GEHL[1], Khaled TAALAB[2], Dina D'AYALA[3] and Tao CHENG[4]

ABSTRACT

This paper aims at presenting some preliminary results from the European FP7 INFRARISK project (Novel Indicators for identifying critical INFRAstructure at RISK from natural hazards), which final objective is to develop stress-tests on European critical infrastructure, namely road and rail networks. More specifically, several approaches for the derivation of fragility functions for roadway bridges are proposed and discussed here. First, a generic test bridge from earlier work by Nielson (2005) is selected and modelled: this mock-up is used throughout the study, as it is sufficiently straightforward to enable non-linear modelling and computation, while still complex enough to include most of the structural components that are usually found in bridges. Parallel to the fully detailed bridge model, a simplified model composed of macro-components, which are modelled as zero-length non-linear springs in the OpenSees platform, is also introduced for simplification purposes. Then the bridge is subjected to a series of synthetic ground motions and the corresponding analytical fragility curves are derived using the state-of-the-art system reliability approach, where the system's fragility is assembled from the component fragilities and their respective correlation. Due to the computational difficulties that might arise from the modelling of large and complex bridge structures, an alternative approach is introduced and its actual feasibility is discussed: this so-called "component-by-component" approach consists in the estimation of the fragility of each component without requiring the full non-linear computation of the rest of the bridge system. The derivation of conditional fragility curves for each component given the damage state of the rest of system, as well as the careful construction of the Bayesian network of the failure sequence of the bridge's components, appear to be promising and feasible steps towards the development of the global fragility functions for the whole system. Complementary to this bottom-up approach, an empirical exploitation of available fragility curves is planned in order to predict the fragility of bridge typologies which have not yet been studied. To this end, an empirical model based on support-vector machines (SVMs) is used to analyse large numbers of interacting variables and investigate the effect of some typological parameters on the final fragility curves.

INTRODUCTION

The resilience of the main road and rail transportation networks across Europe has become increasingly critical in recent years, due to the growing pressure that is put on their use, as well as the exposure to a variety of natural hazards (e.g. earthquakes, landslides, rock falls, floods, etc.) over the large areas covered by these transportation networks. In this context, the European FP7 INFRARISK

[1] UCL, Dept of Civil, Environmental and Geomatic Engineering, EPICentre, London, UK, p.gehl@ucl.ac.uk
[2] UCL, Dept of Civil, Environmental and Geomatic Engineering, London, UK, k.taalab@ucl.ac.uk
[3] UCL, Dept of Civil, Environmental and Geomatic Engineering, EPICentre, London, UK, d.dayala@ucl.ac.uk
[4] UCL, Dept of Civil, Environmental and Geomatic Engineering, London, UK, tao.cheng@ucl.ac.uk

project aims to develop reliable stress tests on critical road and rail infrastructure through an integrated multi-risk framework that accounts for coupled interdependencies, spatio-temporal processes, cascading effects and time dependent vulnerability.

The analysis of a whole infrastructure system is usually carried out by breaking down the network into a set of components that have similar features or functions in the system (e.g. sets of bridges, tunnels or road pavements in the case of a road network system). The vulnerability and functionality of each of these objects can then be assessed, leading to an estimation of the performance of the network system based on the state of its components. This bottom-up approach has been detailed, for instance, in the recent FP7 SYNER-G project, where an object-oriented architecture has been specifically developed for the seismic analysis of interdependent infrastructure systems (Cavalieri et al., 2012). In the present study, the same logic is used, while focusing also on the assessment of "lower-level" elements, in the sense that road network components such as bridges are decomposed into a set of sub-components like piers, decks or abutments. This approach has been previously used for the seismic fragility analysis of bridges (e.g. Nielson and DesRoches, 2007; Song and Kang, 2009), where system reliability tools allow the computation of the global fragility of the whole component based on the fragility of its sub-components. A fault-tree analysis of the bridge constitutes a first step to understand the relative contribution of each subcomponent to a given failure mode (i.e. whether some sets of sub-components are to be considered in a series or parallel system). Correlation or independence between the different failure events of sub-components has also to be accounted for (Song and Kang, 2009). The aforementioned approach is first applied to the well documented and studied model of a multi-span simply supported concrete roadway bridge, as detailed by Nielson (2005). To this end, and in order to ease the execution of numerous nonlinear time-history analyses, a macro-model of the bridge system is first proposed using a set of zero-length springs to represent the behaviour of each of the bridge components.

While the widely used system reliability approaches still rely on the nonlinear analysis of the whole system and the subsequent identification of its components' fragility, it is proposed here to directly assess the response of each component without requiring the use of a nonlinear model for the entire bridge system. For each component, the proposed method is based on the definition of boundaries forces that represent the behaviour of the rest of the bridge system. The nonlinear response of the other components is updated through the identification of the first modal shape of the bridge system: this is done by computing the nonlinear vibration modes for each component's limit state. A Bayesian network framework can then be used to assemble the global failure probability of each component by using the specific failure probabilities given the state of the other components. This original approach is applied to some extent to the macro-model of the multi-span simply supported concrete bridge by Nielson. The proposed framework is expected to provide several improvements in the fragility assessment of large infrastructure components. First, the use of a reduced bridge model and the segmentation of the nonlinear response into sets of linear bridge configurations dramatically reduce the computation time and the convergence issues that usually arise with large finite element models. Secondly, in the context of the INFRARISK project, where earthquake-induced ground failure events or coincidental hazards like floods are accounted for, this approach is expected to prove much more flexible in terms of multi-hazard vulnerability assessment. The final goal of this study would be to assess the feasibility of creating a catalogue of fragility functions of bridge components in various configurations, which could then be applied and assembled to a wider range of bridge systems.

The last section of this paper proposes a work plan for future developments within the INFRARISK project. Aside from the necessary further developements that are to be carried out in order to achieve the proposed component-by-component approach, the use of support vector machines for the analysis of existing fragility functions will be presented. This approach is based on the analysis of the different parameters that define a given bridge typology (e.g. materials, connection types, design level, number of spans, etc.) and it will aim at quantifying their respective influence on the fragility of each typology.

FRAGILITY ANALYSIS OF A ROADWAY BRIDGE

This section presents the model of the selected bridge, as well as the various approaches that are proposed for the fragility assessment of the bridge system and its components.

Presentation of the bridge model

The proposed approaches are first demonstrated on a well-defined model of a generic highway bridge, as described by Nielson (2005): the chosen typology is a Multi-Span Simply Supported Concrete (MSSSC) girder bridge. The finite element model of this bridge has been assembled using the OpenSees platform (McKenna et al., 2000), as shown in Fig.1. It is composed of three spans, which are supported by two multi-column bents: each bent comprises three 4.6m high columns with a circular section, which support a 12.81m long rectangular beam. The two side spans are 12.2m long and the middle has a length of 24.4m. Each of the eight deck girders are connected to the multi-column bents through fixed or expansion bearings (one of each type at each end). At the bridge extremities, pile-bent girder seat type abutments are considered. Finally, pier foundations are modelled through linear elastic translational and rotational springs.

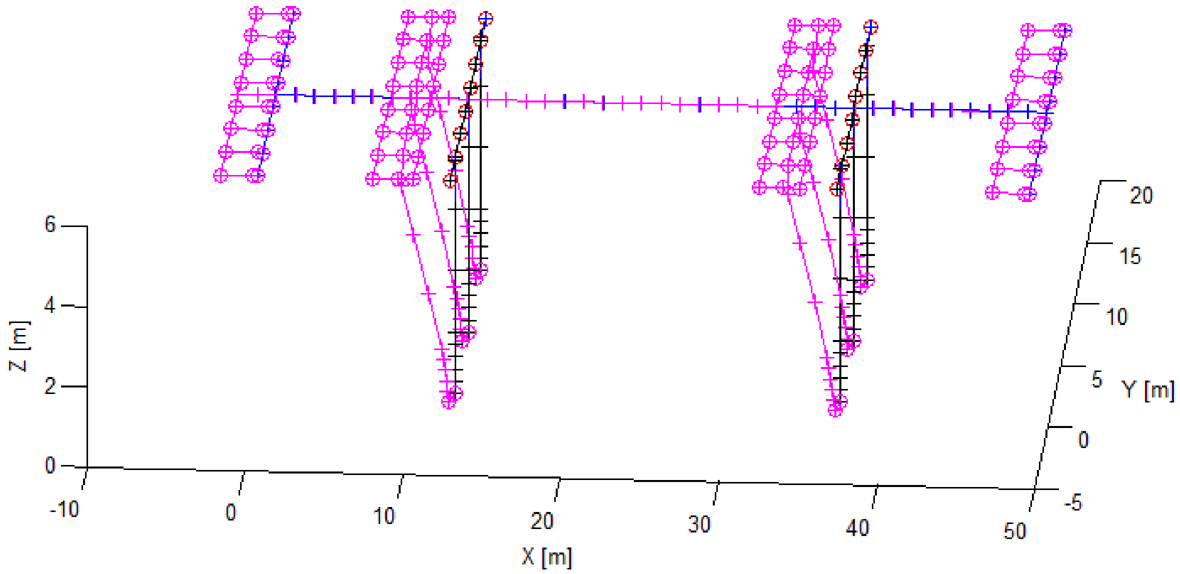

Figure 1. Finite-element model of the MSSSC girder bridge (Nielson, 2005). The structure in red represents the first mode shape (with eigen-period $T_1 = 0.64$s).

The bridge system can therefore be decomposed into the following components, each of them possessing their own constitutive laws and limit states:

- Multi-column bent (**#COL**): this component is the result of the assembly of the foundation (spring element), the column piers and the transverse beam (nonlinear fiber section element). The reinforced concrete beams and columns are assembled using the *Steel01* and *Concrete01* materials in Opensees). The global behaviour of this component is shown in Fig.2a.
- Abutment (**#AB**): Abutments are modelled with a nonlinear spring through an asymmetric behaviour. In tension (active behaviour), only the abutment piles are resisting the applied forces, while in compression (passive behaviour), additional resistance is provided by the soil back-fill. The associated behaviour is presented in Fig.2b.

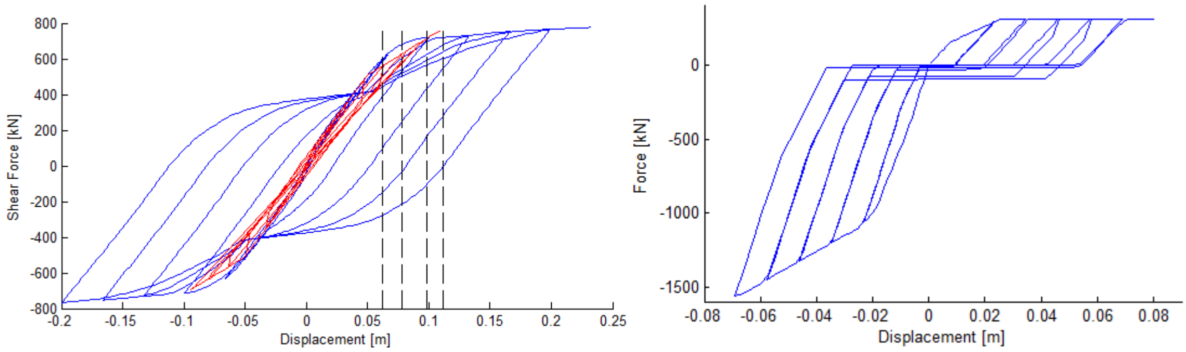

Figure 2.Cyclic pushover curves of the pier (left) and abutment (right) components along *X*-axis. The curve in red represents the approximated hysteretic tri-linear model, and the dashed vertical lines the damage threshold for the pier component.

- End span fixed bearing (**#BEfix**): bearings for this bridge type are elastomeric pads associated with steel dowels. The global behaviour (see Fig.3a) therefore results from the combination of a friction law (for the elastomeric pad) and a hysteretic law (for the steel dowel). Fixed bearings are allowed a 3.2mm displacement in either direction before the steel dowel is activated.
- End span expansion bearing (**#BEexp**): they present the same characteristics as above, except the allowed displacement is now 25.4mm (see Fig.3b).
- Middle span bearings (**#BMfix** and **#BMexp**): these bearings support the heavier middle span and the friction law presents higher initial stiffness and friction coefficient (see Fig.3cd). Fixed and expansion bearings allow the same displacement gaps than for the end span bearings.

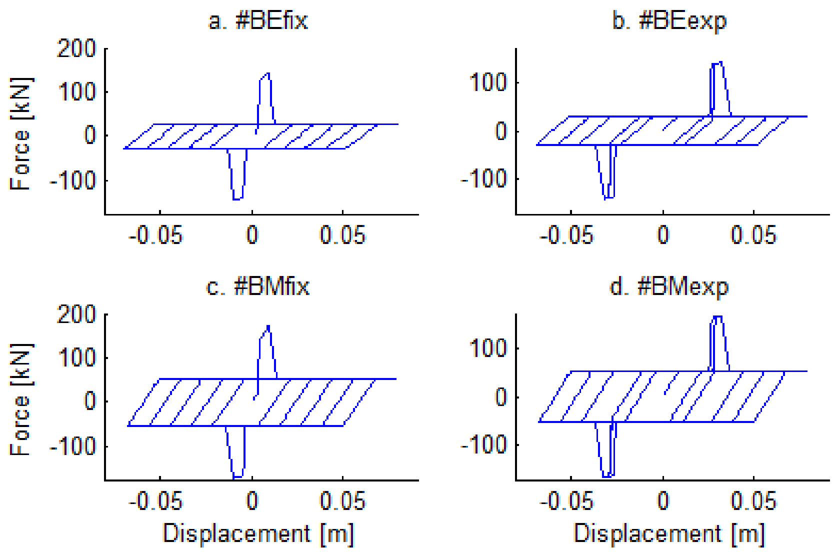

Figure 3.Cyclic pushover curves of the bearing components along the *X*-axis.

Based on the definition of the above components, a simplified bridge model is proposed: all components are modelled by zero-length spring elements (see Fig.4), whose behaviours are approximated by piece-wise linear curves that are based on the constitutive laws presented above. In the case where the bridge is only loaded in the longitudinal direction (i.e. *X*-axis in Fig.1), the symmetry properties of the system prevent any torsion effects: the different bearing and abutment elements, which are assembled in parallel (i.e. eight elements at each *X* location, one for each girder) can be assumed to provide very similar displacement values. Each type of bearings and abutments is therefore grouped in order to create a macro-component, which possesses eight times the stiffness and strength of each single component. The masses of the bridge system are lumped to five nodes, as detailed in Table.1.

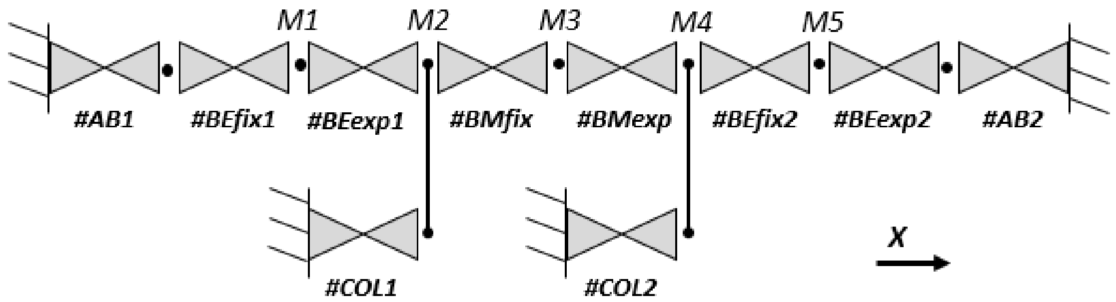

Figure 4. Proposed macro-model for the bridge system. The zero-length springs are represented by the grey triangles. The numbers M1 to M5 represent the masses assigned to each node.

Table 1. Lumped masses assigned to the nodes of the macro-model

Node	Mass of	Value (tn)
M1	end span	115.41
M2	pier 1	69.8
M3	middle span	316.63
M4	pier 2	69.8
M5	end span	115.41

While the bearing and abutment components are already associated with a piecewise hysteretic behaviour, they can be used as is in the macro-model. The pier component has been approximated by a tri-linear hysteretic behaviour (see Fig.2a), where parameters such as the slope of the reloading curve or the position of the knees have been optimized to fit closely the response of the fully modelled under nonlinear dynamic loading. The dynamic response of both models, which have been submitted to a group of fifty ground motions, is shown in Fig. 6: the scatter of points reveals a good agreement between both models, and the use of an equivalent spring to model the whole pier component seems to prove a reasonable approximation over the range of intensity measures that is expected for this generic bridge model. Such a simplification is mostly motivated by the drastic reduction of computation time that is provided by the spring model (factor 100 at least). Finally, the bridge macro-model presents a fundamental period of 0.66s, which is similar to the one of the detailed finite element model (i.e. 0.64s).

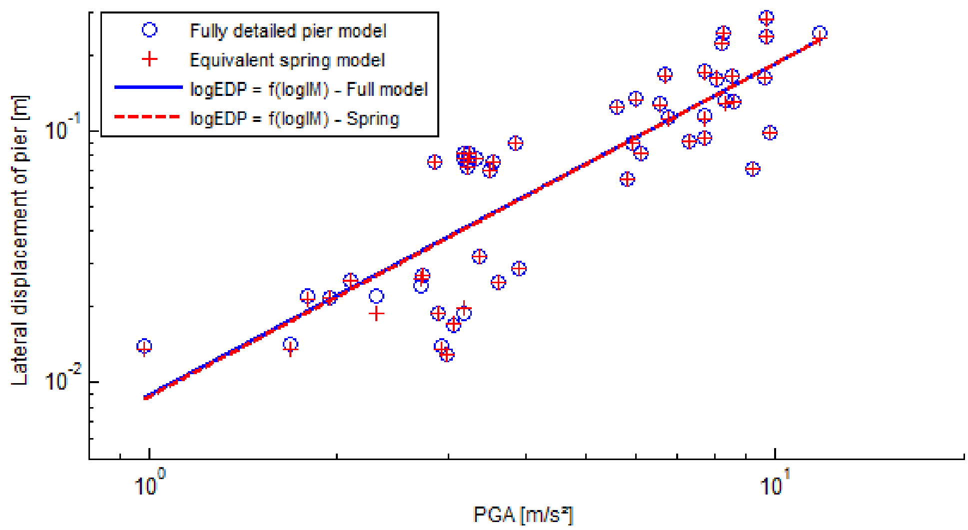

Figure 5. Comparison of the response of both models when subjected to a set of fifty ground motions

System reliability approach

As a first step, a standard system reliability approach (Song and Kang, 2009; Kang et al., 2008) is used to assess the fragility. In this context, the bridge system may be regarded as a series system of its components: the failure of one of the components will trigger the failure of the whole system. Let us consider a given damage state *DS* and a number *N* of bridge components. According to Kang et al. (2008), the sample space can be decomposed into a set of $n = 2^N$ mutually exclusive and exhaustive (MECE) events. Each of the system events can therefore be represented by an event vector $\boldsymbol{c}$, where the elements represent the involvement or not of each basic MECE event to the system event. Since the bridge is considered as a series system, the probability of the system reaching or exceeding DS_j can then be expressed as a combination of all possible configurations of component failures. In the present case, where components are interacting within a structural system and are subjected to the same ground motion, the MECE events cannot be considered as statistically independent events and the system probability P(*DS*) cannot just be expressed as the sum of the basic event's probabilities. Instead, a vector $\boldsymbol{X}$ of random variables has to be introduced in order to represent the statistical dependence between the components (Song and Kang, 2009):

$$P(DS) = 1 - P(\overline{DS}) = 1 - \int_x c^T p(x) f_x(x) dx \tag{1}$$

Where $p(\boldsymbol{x})$ represents the conditional probability vector of the basic MECE events given the variable $\boldsymbol{x}$, and $f_x(\boldsymbol{x})$ the joint probability distribution function of $\boldsymbol{x}$. One efficient way to represent the random variables $\boldsymbol{x}$ is to use the Dunnett-Sobel class of variables (Dunnett and Sobel, 1955), as proposed by Song and Kang (2009). This decomposition enables to represent the standardized response Z_i of component *i* as a combination of two standard normal variables U_i and X:

$$Z_i = \sqrt{1 - r_i^2}\, U_i + r_i X \tag{2}$$

Where r_i is the approximate expression of the correlation coefficient between the bridge components: the factors r_i can be numerically approximated by running an optimization routine in order to minimize the error between the actual correlation coefficient ρ_{ij} and the product $r_i.r_j$, for each couple of coefficients *i* and *j*. Finally, assuming that the failure probability of each component take the analytical form of a lognormal cumulative distribution function, the system's probability of failure can be expressed by the following integral, which can be solved numerically:

$$P(DS|IM) = 1 - \int_{-\infty}^{+\infty} \prod_{i=1}^{n} \left[1 - \phi\left(\frac{\log IM - \log \alpha_i + \beta_i r_i x}{\beta_i \sqrt{1 - r_i^2}} \right) \right] \varphi(x) dx \tag{3}$$

Where α_i and β_i are the component fragility parameters, and ϕ and φ are the standard lognormal and normal cumulative distribution functions, respectively.

The procedure summed up above is then applied to the bridge macro-model, which is submitted to a set of 144 synthetic ground motions. In order to be consistent with the seismo-tectonic context of the area where the bridge has been modelled (i.e. Central Southern United States), the generation of the ground motions follows the magnitude – epicentral distance criteria that are prescribed in Nielson (2005). The synthetic signals have been generated using a stochastic procedure developed by Pousse et al. (2006), which is an extension of the method of Sabetta and Pugliese (1996). Due to clarity and conciseness concerns, only one limit state is presented here, namely the "slight" damage state proposed by Nielson (2005), as detailed in Table.2. It should be noted that the damage measure for the concrete columns is initially expressed though the section curvature: a conversion to lateral displacement had to be made, in order to obtain a damage measure that is measurable with the use of the equivalent spring model.

Table 2. Proposed limit-states for "slight" damage, based on Nielson (2005)

Component	Damage measure	Median value	Standard –deviation (β_{DS})
Concrete column	deformation [m]	0.0625	0.59
Fixed bearing	deformation [m]	0.0289	0.60
Expansion bearing	deformation [m]	0.0289	0.60

Abutment (active)	deformation in tension [m]	0.0098	0.70

The correlation matrix of the logarithm of the components' responses (see Table.3) is then used to build the Dunnett-Sobel class of random variables. An optimization process using the Matlab program has led to the identification of the vector of correlation factors r_i: [0.8470;0.8218;0.9062;0.7855;0.9701;0.7804;0.9902;0.9776;0.9697;0.9697], in the same order as in Table.3.

Table 3. Correlation matrix between the logarithms of the response of each component

Component	#AB1	#BEfix1	#BEexp1	#BMfix	#BMexp	#BEfix2	#BEexp2	#AB2	#COL1	#COL2
#AB1	1	0.6587	0.9298	0.7936	0.8767	0.6885	0.8348	0.8527	0.8534	0.8477
#BEfix1		1	0.6939	0.5979	0.8678	0.7272	0.8971	0.8659	0.9063	0.8974
#BEexp1			1	0.7599	0.8724	0.7571	0.8814	0.8685	0.8919	0.8885
#BMfix				1	0.8038	0.6264	0.7489	0.7574	0.7310	0.7558
#BMexp					1	0.7568	0.9346	0.9516	0.9511	0.9445
#BEfix2						1	0.7620	0.7488	0.7709	0.7669
#BEexp2							1	0.9249	0.9900	0.9962
#AB2								1	0.9436	0.9352
#COL1									1	0.9947
#COL2										1

Finally, the correlation results can be injected in Equation 3 and the fragility curve for the whole bridge system is numerically estimated and plotted in Fig.6.

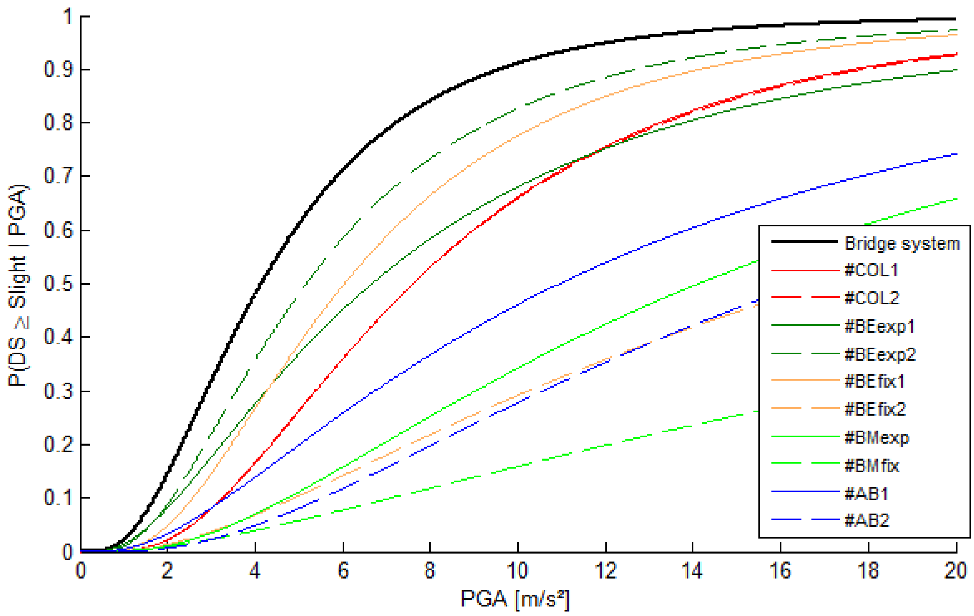

Figure 6. Fragility curves of the bridge system and its components for Slight damage state, using the system reliability approach.

At the current stage, comparison with the fragility curves from Nielson (2005) may prove difficult, due the use of different sets of ground motions for the dynamic analyses and the different assumptions in the bridge model: currently, the model presented here does not account for the possibility of collisions between deck elements, while an impact element has been implemented in Nielson (2005). Also, it is interesting to note that the actual position of the component within the bridge system seems to have a significant impact on their behaviour, and therefore their fragility. For instance, in the case of fixed bearings, the one that is located at the very extremity of the bridge (i.e. #BEfix1) appears to endure the highest deformations, as opposed to component #BMfix, which is located in the middle of the bridge, between the two piers. This observation implies that the investigation of the specific response of each component within the system is indeed necessary, even for those components that have the same characteristics and limit states. For a given component, the beneficial or detrimental influence of its immediate environment, namely the adjacent components, should therefore be studied in a more systematic manner.

Component-based approach

While the system reliability approach presented above has proven to be an efficient and straightforward way to assess the fragility of a large structural system such as a bridge, one major point is that this method still requires the modelling and the nonlinear computation of the whole structural system, before being able to estimate the "component" fragility curves. Although this task is not an insurmountable issue in the case of the present bridge model, the computational efforts and the related convergence issues might make it more difficult for much larger bridge structures that span over hundreds of meters and include tens of piers and decks. Therefore the purpose of this section is to study the feasibility of an approach that would only require the nonlinear computation of one fraction of the bridge at a time: this method would lead to the derivation of actual component fragility curves, which would be declined for different configurations and for different combinations of damage states. Then it is expected that the careful study of the failure sequence within the bridge system (i.e. the order in which each component fails) will help to build an adequate Bayesian belief network in order to combine the different conditional probabilities (i.e. component fragilities) into the global fragility of the bridge system.

The first step is to assess the conditional fragility of each component one by one, while the rest of the bridge system is modelled through the use of springs in different configurations of damage, in order to reproduce the behaviour of the neighbouring environment. In this context, the notion of damage states, which are usually based on considerations of usability or performance objectives, must be based on the knees that compose the piecewise linear behaviour of each component. When all the other components are assumed to be in the intact damage state (i.e. initial elastic behaviour), this process is trivial since the original springs (see Fig.4) can be used directly. However, when one or more components are in a given damage state, the difficulty resides in the definition of linear springs that would represent the behaviour of the damaged components. The first option that comes to mind is the use of an equivalent secant stiffness, which would be based for instance on the median deformation that is characteristic of each damage state. While the use of the secant stiffness may represent a sound approximation in the case of a static analysis, a few tests have shown here that it is not valid for dynamic analyses, where the estimated displacements are usually underestimated with respect to the ones obtained with the complete nonlinear model: the correct displacement would have to be obtained via several iterations by updating the displacement and the associated stiffness, like it is advocated by the Secant Method (ATC, 1996; Paret et al., 2004). However, such a process would require to perform a series of successive linear dynamic analyses, which might not be necessarily advantageous with respect to one nonlinear dynamic analysis.

In the case of a multi-degree-of-freedom system such as a bridge, the damage of one component (i.e. reduced tangent stiffness) will have the effect of concentrating most of the deformations on this component, while the other ones will be less solicited by the seismic vibration. While this effect seems to be largely underestimated with the sole use of the secant stiffness, it appears that the estimation of the nonlinear modes of the structural system may provide useful knowledge on the way the system behaves in each damage state. Nonlinear modal analysis has been applied to a limited set of examples in the past (Jiang et al., 2004; Pierre et al., 2005): it aims at quantifying the evolution of the modal shapes and periods as a function of modal amplitude, when the stiffness matrix of the system is susceptible to evolve with the level of deformation. As an example, the modal evolution of the bridge model in Fig.4 is evaluated by considering the components #COL1, #COL2, #BEexp1, #BEexp2 and #BMexp as nonlinear, the rest of them being assumed as linear for simplification purposes. In the case of piecewise linear models, only the second segment is considered in the nonlinear domain for now, thus reducing all the models to bi-linear models. The evolution of the first modal shape is represented in Fig.7, where it can be observed that the contribution of each component varies with the "damage" configuration of the system.

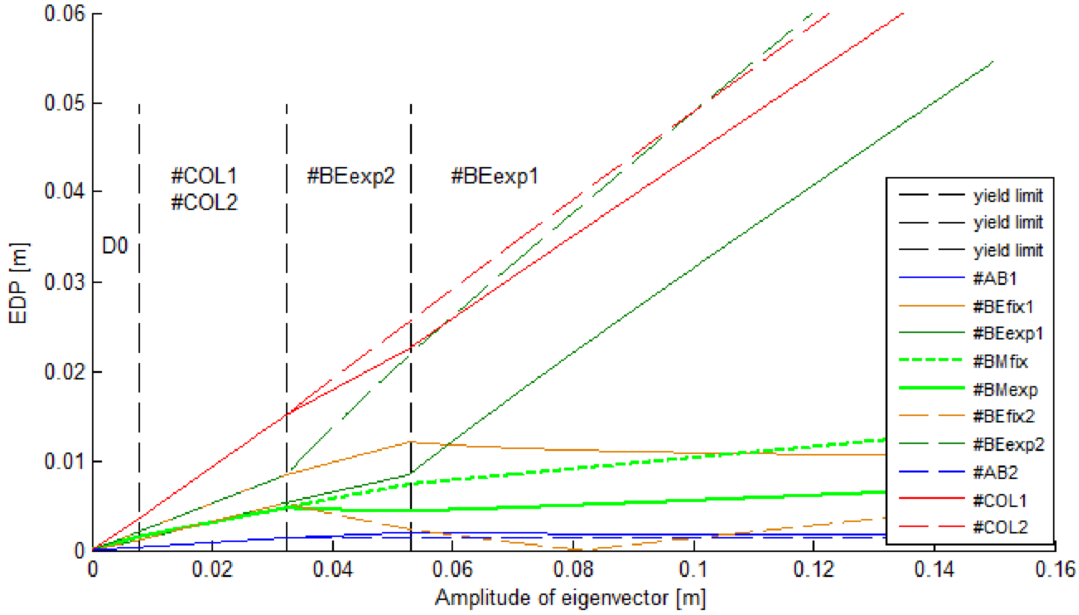

Figure 7. Evolution of the contribution of each component to the modal shape of the first nonlinear mode. The vertical dashed lines indicate the entry of each successive component into the nonlinear domain.

The observed failure sequence from Fig.8 follows closely the one that happens when the considered model is subjected to a set of nonlinear dynamic analyses, showing that the first mode is predominant for this structural system. Moreover, the comparison between the contributions from each component and the median relative responses obtained from the nonlinear analyses (see Fig.8) show a good agreement for each "damage" interval.

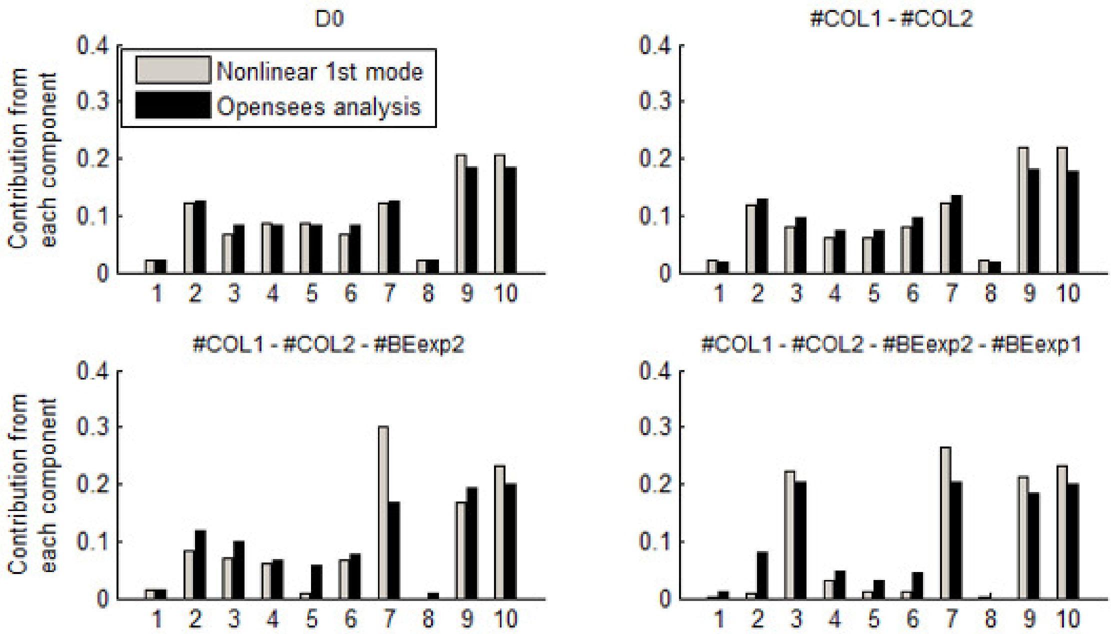

Figure 8. Evolution of the nonlinear modal contribution from each component (in relative displacement) for each discrete damage interval and comparison with the median results from the OpenSees nonlinear dynamic analyses.

The results from Fig.8 are encouraging in the sense that the nonlinear modal analysis can be run in a few tens of seconds and it can give an accurate idea of which components are the most solicited for each damage configuration. However, nonlinear modal analysis is unable to provide information on the actual level of seismic intensity that corresponds to the different damage intervals, since only relative values in terms of contribution to the main eigenvector are computed. The results from the nonlinear modal analysis could still be used to approximate the baseline behaviour of the bridge system for different combinations of its components' states.

Finally the last step of this component-by-component analysis would reside in the construction of a Bayesian Network (BN) that follows the identified failure sequence. One issue resides in the existence of nonlinear coupling between components or closely correlated responses, which would require the use of cyclic graph, a feature that is in contradiction with the BN theory and that prevents the use of many of the inherent properties of directed acyclic graphs. This issue could be solved by grouping the closely correlated component events in a single Bayesian node, however at the risk of underestimating probability of occurrence of one of the events. A more accurate approach would be to introduce a Dunnett-Sobel class of random variables as extra nodes in the BN, in order to eliminate the cyclic relations. Such strategies are detailed by Bensi et al. (2011) in the case of correlated Gaussian random fields. Some importance measures are also proposed, enabling to adjust the size of the BN by removing the links and nodes that would imply the lesser loss of accuracy.

As an example, the "damage" (i.e. defined here as the first knee in the piecewise linear behaviours) sequence of the bridge components when subjected to the 144 ground motions is presented in Fig.9a. It appears that for several components, there is no overlapping between the damage events, meaning that, over the whole set of dynamic results, if component A precedes component B in the failure sequence, then each time component B is damaged, A is damaged as well, and reciprocally for the intact state (i.e. A intact implies that B is intact): in this configuration, the corresponding BN can be simplified and only one directed link is needed. On the contrary, for the other components, the failure sequence is not rigorously respected for all ground motions (i.e. presence of some overlapping), which requires to account for nonlinear coupling between the components. In the present example, the corresponding BN that is derived from the failure sequence is proposed in Fig.9b. Each link in the proposed Bayesian network will require the derivation of two conditional fragility curves, given the discrete state of the parent node in the BN. Since there fragility curves will be computed using an equivalent linear bridge model, it is then expected to witness significantly lower computation times compared to a full non-linear analysis of the system.

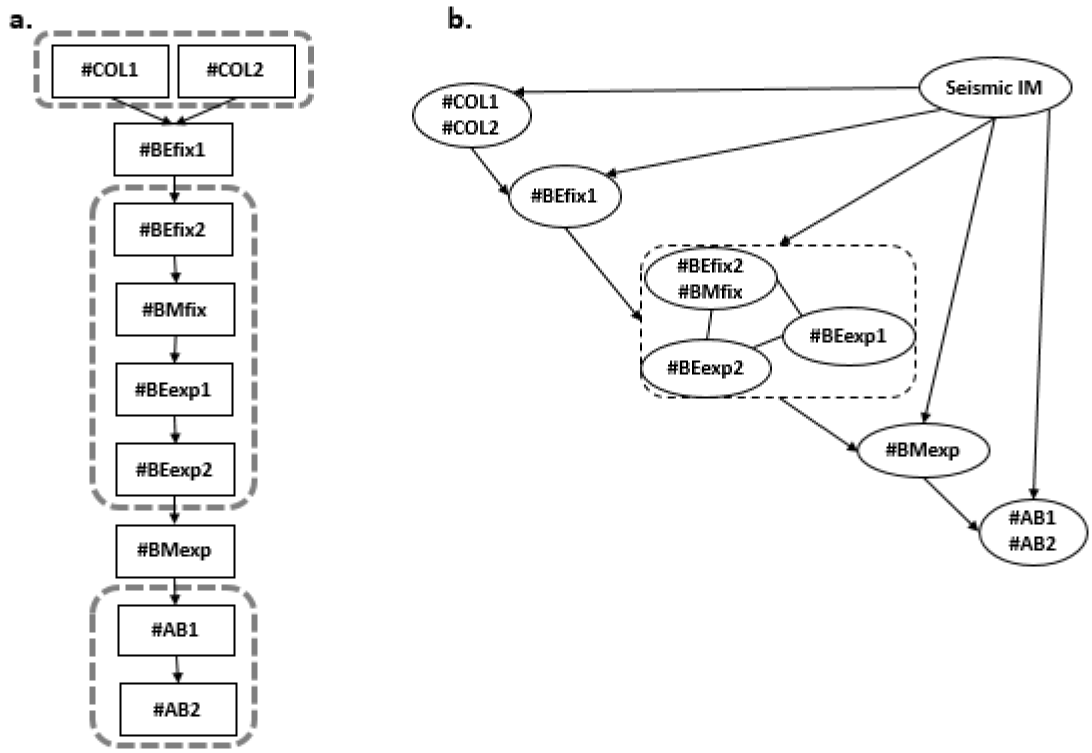

Figure 9. Damage sequence of the bridge sequence (left) and corresponding Bayesian network formulation (right). The dashed contours in grey indicate overlapping damage events and require specific treatment to remove the corresponding cycle in the BN.

FUTURE DEVELOPMENTS

As this paper demonstrates, the use of component-based fragility curves is a promising development in modelling the relationship between earthquakes and bridges. Modelling individual components is, however, a time consuming process. An alternative and complementary approach is to investigate the efficacy of an empirical modelling approach which uses pre-existing fragility curves to predict the fragility of bridges which have not been modelled. The SYNER-G project identified the main bridge typologies in Europe and developed both a new taxonomy and a new set of fragility functions for a number of representative case study bridges (Crowley et al., 2011). This has created a database which contains information about the bridge components (material, deck type, pier connections etc.) and fragility curves for a number of limit states. In total, up to 17 different components are record in the SYNER-G database, as well as some ancillary conditions, such as the propensity of soil to liquefaction. Much like the analytical component-based model, the empirical model advocates a component-based approach to fragility. It uses a machine learning algorithm to develop relationships between components (and combinations of components) and overall fragility of the bridge as modelled by SYNER-G. As well as predicting the overall fragility of the bridge, the empirical model will also provide a rank of the components, which suggests which is most influential on the total fragility.

The empirical model proposed for this study is support vector machines (SVMs). SVMs perform classification (and regression) by constructing N-dimensional hyperplane that optimally separates data into categories (Hearst et al., 1998). For scenarios, such as infrastructure, where there are a huge number of interacting variables to consider, SVMs transform data to make it linearly separable and hence can handle highly complex datasets. This approach has been successfully applied to the spatio-temporal prediction of tornado occurrence (Adrianto et al., 2009) and landslide susceptibility (Ballabio and Sterlacchini, 2012). Furthermore, if the data became available, it is possible to include a suite of environmental, topographic and climatic variables, which could impact on overall fragility in the real world. As a case study, we will use the models developed using the SYNER-G dataset to predict the fragility of the bridge described in this paper (Nielson, 2005). This will allow a direct comparison of the results and promote discussion regarding the relative influence of each component. It is the proposal of this study that the two modelling techniques are complimentary. The SVM models can offer empirical validation and in turn, the fragility curve models will provide component-level explanation of the performance of transport infrastructure given hazards of different magnitudes.

CONCLUSIONS

By way of a closing remark, this study has presented some of the possible approaches to assess the fragility of large structural system such as roadway bridges. Selecting a generic bridge model from the work by Nielson (2005) as a first case-study, a system reliability approach has been implemented to the bridge system: the results account for the correlation between the components' responses and one interesting observation lies in the different behaviour and vulnerability experienced by components that possess the same inherent mechanical properties, but on different spatial locations of the system. Also, the need for a full non-linear dynamic analysis of the entire system in order to assess the system reliability may prove problematic in the case of very large structural systems, such as bridge that may span over several hundred of meters. For this reason, an alternative approach has been investigated, where fragility curves for each component would be derived separately, while accounting for the surrounding structural environment: this could be achieved by defining conditional fragility curves for each component, given the configuration and the structural state, in terms of damage levels, of the of the bridge system. Based on a careful evaluation of the failure sequence of the components within the system, a Bayesian network within a minimum set of probabilistic links could then be proposed in order to assemble the different conditional probabilities into the system(s global fragility function. While the failure sequence has been identified here through a set of analytical results, future developments could also include an expert elicitation framework, where a selected group of experts could formulate their opinion on various failure sequences for different bridge typologies. Such a process would also be beneficial for the identification of model uncertainties, since different failure sequences could lead to different Bayesian network structures and, therefore, different fragility formulations. Finally, as an alternative to the component-by-component approach, a more global analysis of the database of available fragility curves for bridge systems will also be investigated: data mining tools such as support vector machines could be used to quantify the influence of various typological parameters and predicted failure probabilities for bridge typologies that have been studied in details yet.

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