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UNCERTAINTY EVALUATION OF CIVIL ENGINEERING STRUCTURES BEHAVIOR

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Structural behavior, Uncertainty, Backanalysis, Model updating, Probabilistic analysis

ABSTRACT

All decisions that concern the development and management of existent infrastructure are of extremely importance for society. However, it is verified that these decisions are influenced by a huge source of uncertainties that must be taken into account. A methodology that consider this, and, which objective, is to support such decisions, is developed within this research. In order to support such methodology, a numerical model is developed. Such model is then calibrated using backanalysis procedures, so that, given results, could best fit obtained experimental data. The developed model is continuously updated with collected data, by using inference processes. Then, a full probabilistic analysis is performed in order to evaluate the respective structure behavior. This paper describes such methodology, and the respective application with a batch of reinforced concrete beams, tested at laboratory, till failure. The developed methodology is applied with success and obtained results revealed the respective importance in future decisions concerning the societal infrastructure. Further steps consider the application of such methodology with a real structure.

INTRODUCTION

The development and management of the societal infrastructure is a central task for the continued success of society. The decision processes involved in this task concern all aspects of managing and performing the planning, investigations, designing, manufacturing, execution, operations, maintenance and decommissioning of objects of societal infrastructure, such as traffic infrastructure, housing, power generation, power distribution systems and water distribution systems. The main objective from a societal perspective by such activities is to improve the quality of life of the individuals of society both for the present and the future generations.

Decision making for the purpose of assessing and managing the risks should be seen relative to the occurrence of hazards, i.e., risk management in the situations before, during and after the event (JCSS 2008). This is because the possible decision alternatives or boundary conditions for decision making change over the corresponding time frame. Before a hazard occurs the issue of concern is to optimize investments into so-called preventive measures such as e.g. protecting societal assets, adequately designing and strengthening societal infrastructure as well as developing preparedness and emergency strategies. During the event the issue is to limit consequences by containing damages and by means of rescue, evacuation and aid actions. After a hazard, the situation is to some degree comparable to the situation before the event; however, the issue here is to decide on the rehabilitation of the losses and functionalities and to reconsider strategies for prevention measures.

If all aspects of decision problem would be known with certainty, the identification of optimal decisions would be straightforward by means of traditional cost-benefit analysis. However, due to the fact that our understanding of the problems involved in the decision problem is often far less than perfect and that we are only able to model the involved processes of physical phenomena as well as human interactions in rather uncertain terms, the decision problems in engineering is subject to significant uncertainty. Due to this, it is not possible to assess the outcomes of decisions in certain terms. There is so, no way to assess with certainty the consequences resulting from decisions we take. Accordingly, there is not one certain optimal decision but a set of feasible decisions which are acceptable. However, this interval can be reduced as the knowledge about studied societal infrastructure increases. Analyzing Figure 1, by minimizing such interval, the possibility of taking the right decision, the one that maximizes the respective utility, is higher.

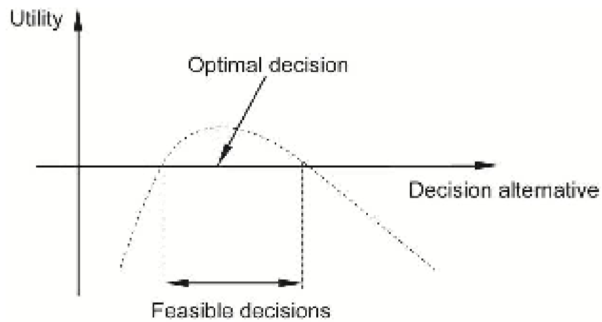

Figure 1:Decision vs. Utility

A methodology for the evaluation of any societal infrastructure that considers both uncertainty and variability sources, present in numeric and experimental data, is developed within this research. Such methodology is based in a numerical model, which can be used to support any decision before, during and after the hazard, and that can be updated and calibrated in a continuous way as more information regarding the studied infrastructure is collected.

METHODOLOGY

Figure 2 presents a flowchart of developed methodology. In order to evaluate the behavior of studied infrastructure, a numerical model is first developed and calibrated with measured data, collected by any implemented monitoring system (measured data T1). In order to do that, critical parameters, the ones that present a higher influence on the structural behavior, are continuously modified so that obtained numerical results best fit measured data. This process is designated by structural identification (St-Id), and defined here as backanalysis T1, was first introduced by Liu and Yao (1978). From several authors that present different applications of St-Id techniques it is important to mention the work of Sanayei and Saletnik (1996a, 1996b), of Banan et al. (2004), of Banan and Hjelmstad (2004), and of Goulet et al. (2009a).

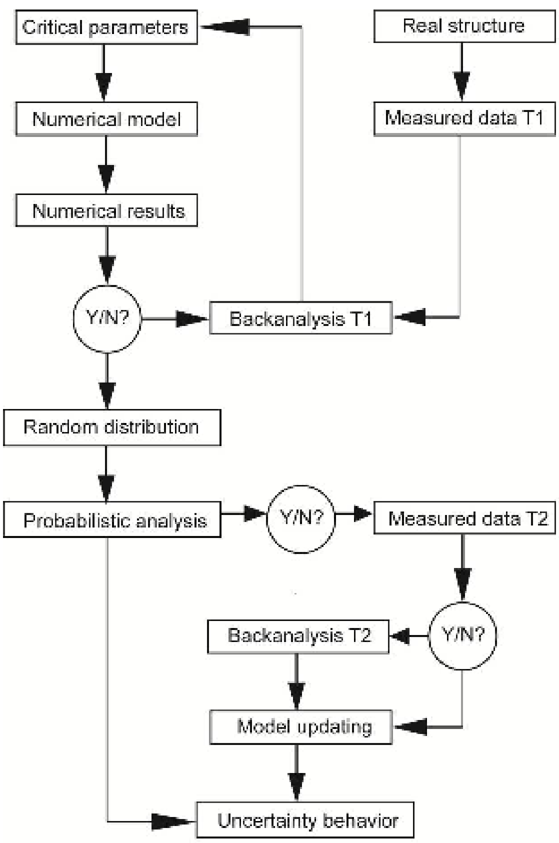

Figure 2: Developed methodology

The backanalysis process is based in a function, designated by fitness function, which determines the difference between numerical results and experimental data (Figure 3):

$$f=\sum_{i=1}^{n}\sqrt{\left(y_i^{*num}-y_i^{*\exp}\right)^2}\Big/\max\left(y_i^{*num}\right) \qquad (1)$$

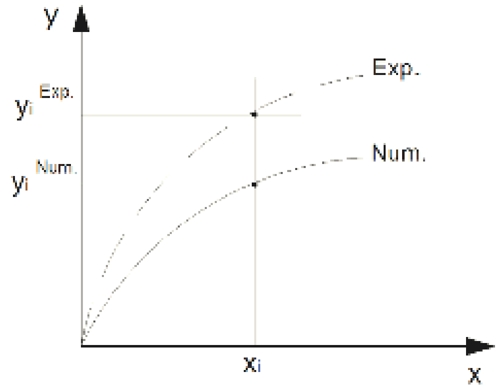

Figure 3: Fitness function

The aim of backanalysis T1 is to minimize fitness function (1). However, such function presents, in several situations, a high non linearity and an extremely large number of critical parameters to be optimized. Minimization process, in this situation, gets longer, presenting a high computational cost, and obtained results that are far from the most suitable ones. In order to overpass such difficulties, different kind of optimization techniques were first tested and the most appropriate one is then chosen.

In a further step, a random distribution is considered for each critical parameter. The mean value is, in this situation, the one obtained from backanalysis T1, being, the standard deviation defined according to existent bibliography (Choi et al. 2004, JCSS 2008, and Matos 2008). A full probabilistic analysis is finally developed, being, the structural behavior, evaluated from a probabilistic point of view.

In some situations there exist additional measurements (measured data T2) that may be considered in previous developed numerical model. In order to perform that, a Bayesian inference concept is introduced (Bernardo and Smith 2004):

$$h(\theta|x)=\frac{f(x|\theta)\cdot h(\theta)}{\int_{\theta}f(x|\theta)\cdot h(\theta)d\theta},\ \theta\in\Theta \qquad (2)$$

where h(θ) indicates the prior distribution, f(x|θ) the likelihood and h(θ|x) the posterior distribution. The prior represents the existent model, the likelihood the collected data and the posterior the updated model. The critical parameters distribution and, consequently, the numerical model are updated by using expression (2) (Figure 4).

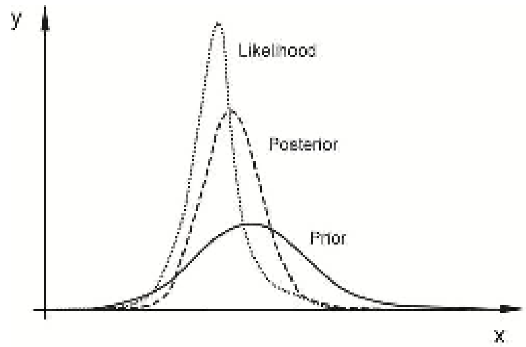

Figure 4: Bayesian inference

Further, a full probabilistic analysis is developed. Sometimes, measured data T2 is considered as indirect. In other words, in such situations, such measurements correspond to parameters that are output of developed numerical model. In these situations a backanalysis T2 may be executed. For these situations, the numerical model is updated in an indirect way. After critical parameters distributions being correctly defined, it is possible, again, to develop a full probabilistic analysis.

The developed methodology will be used with a set of reinforced concrete and composite beams that were tested till failure in laboratory, and, also, with a real structure, a bridge, that was submitted to a load test (Figure 5). In this paper it will be present some results obtained from the application of it with reinforced concrete beams.

Figure 5: Örnsköldsvik Bridge (Sweden)

REINFORCED CONCRETE BEAMS

Experimental data

The presented methodology is validated with two sets of reinforced concrete beams which were tested in laboratory, till failure. The first set is constituted by 36 pinned-pinned reinforced concrete beams (Figure 6) (Matos et al. 2010). During the test it is measured the applied load and the midspan displacement. Studied beams are grouped by typologies, according to the percentage of longitudinal reinforcement, the space between stirrups and the concrete cover. It is used a S500B reinforcing steel and a C25/30 concrete, according to EN 1992-1-1 (2004).

The typology which results are provided in this paper, presents a longitudinal reinforcement of 3ϕ6, a transversal reinforcement of ϕ4@0.10 and a concrete cover of 1.0 cm. This typology includes two laboratory tested beams. The obtained failure mode is bending with concrete crushing (Figure 7). The failure mechanism is characterized by a plastic hinge at midspan.

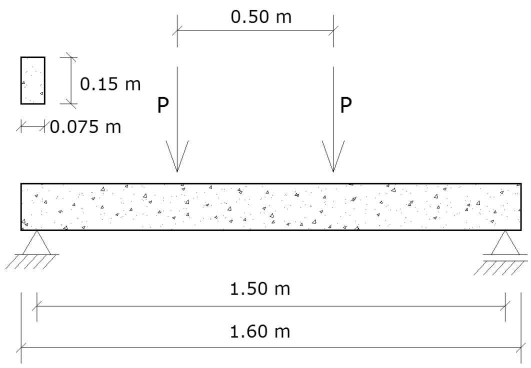

Figure 6: Laboratory test

Figure 7: Bending failure mode

The second battery to be tested is constituted by 32 pinned-fixed reinforced concrete beams (Figure 8). In this situation it was also measured the reaction at simply support. In this situation, tested beams were grouped by typologies, considering the percentage of longitudinal reinforcement, the space between stirrups and the concrete cover. It was used a S500B steel and a C25/30 concrete (EN 1992-1-1, 2004).

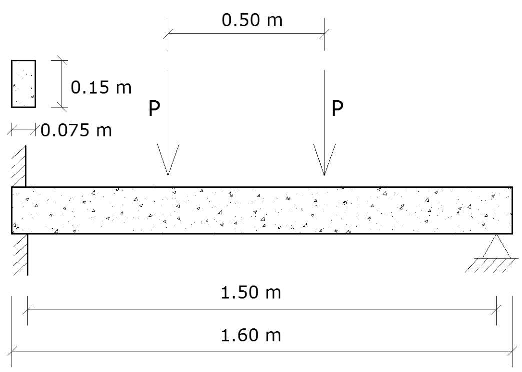

Figure 8: Laboratory test

The typology which results are presented during the analysis, is defined by a longitudinal reinforcement of 2ϕ8 (superior) and 3ϕ6 (inferior), by a space between stirrups of 0.08 m (mid span) and of 0.03 m (supports), and by a concrete cover of 2 cm. This typology includes two laboratory tested beams. The obtained failure mode is bending with concrete crushing. A failure mechanism characterized by two plastic hinges, one at fixed support, and, one other, behind the load which is positioned from the pinned support side, is formed (Figure 9).


Figure 9: Bending failure mode

Numerical model

The non linear numerical model was developed within the platform ATENA (Červenka 2002, Červenka et al. 2002), and with the aim of interpreting obtained experimental data. It was used a quadrangular finite element mesh and a perfect bond between reinforcement and concrete assumed. It was considered a displacement control test.

The developed model was then simplified, without changing the main results, by reducing the finite element and load step number, in order to minimize the respective size, for posterior application of developed methodology (Figure 10). A sensitivity analysis was also performed to identify critical parameters, the ones that present a large influence on the overall structural behavior.

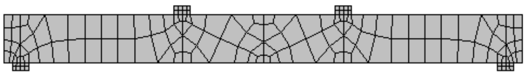
Figure 10: Finite element mesh and results

For the situation of pinned-fixed beams, it was necessary to reproduce the steel beam, in which the actuator applies the load. Also, and in order to simulate the fixed support, which is not working full since the test beginning due to concrete beam accommodation, it were used spring elements (Figure 11).

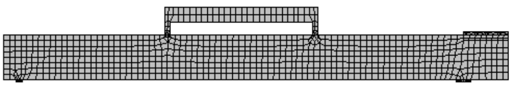
Figure 11: Finite element mesh and results

Backanalysis

The algorithm that was used to perform the backanalysis, by minimizing fitness function (1), is the so called genetic algorithm (Michalewicz 1996, Mitchel 1998, Sawaka 2002). The main idea is to identify, from all possible combinations of values for critical parameters, a set of them that will minimize the distance between numerical and experimental data. This algorithm is a stochastic search technique based on the mechanism of natural selection and natural genetics. In Figure 12 it is presented a flowchart of this algorithm.

Genetic algorithms start with an initial population of individuals generated at random. Each individual in the population represents a potential solution to the problem under consideration. The individuals evolve through successive iterations called generations. During each generation, each individual in the population is evaluated through some measure of fitness. Then, genetic operators (reproduction, crossover and mutation) are applied to create the population of next generation. This procedure continues till the termination condition is satisfied.

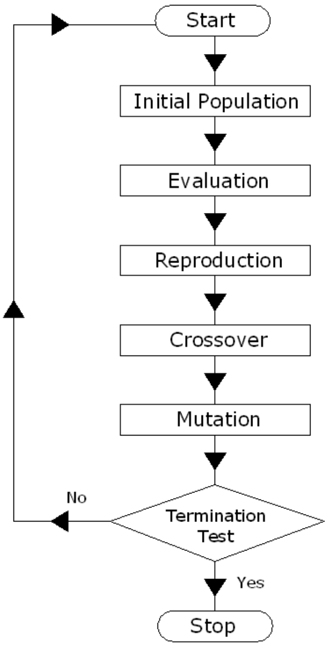

Figure 12: Genetic algorithm

When developing a backanalysis procedure, there are two sources of uncertainties, ones related to experimental measurements and others to numerical analysis, which should be considered. The way such sources are included in the analysis is by considering the global uncertainty value as the algorithm tolerance criteria. In fact, backanalysis can be performed till one limit, the so called precision, determined by such uncertainty sources is achieved.

In order to combine both uncertainties, from numerical and experimental data, and after determining each uncertainty value, the law of propagation of uncertainty (JCGM 100 2008, JCGM 101 2008) is applied. In this situation the correlation coefficient is considered to be null and so a simplified expression is obtained:

$$u^2 = \sum_{i=1}^{n} \left(\delta f / \delta x_i\right)^2 \cdot u(x_i)^2 \qquad (3)$$

where u is the global uncertainty, u(x) the uncertainty related to each item x, and δf/δx the partial derivate of fitness function in order to the item x. By applying expression (3), and by considering the uncertainty values present in bibliography (Goulet et al. 2009b, Goulet et al. 2009c), it is so possible to determine the algorithm tolerance (ε), which is, for analyzed typologies, equal to *6.06* in the situation of pinned-pinned beams and to *16.18*, for fixed-pinned beams. The optimization algorithm is then processed after obtaining the tolerance values. Once the algorithm criterion is achieved, a final population, constituted by different individuals, is obtained. From these individuals, there exists one which presents the best result, respectively, the minimum fitness function value.

Figure 13 presents measured experimental data, and the numerical results obtained by considering the values from EN 1992-1-1 (2004), and the ones obtained from backanalysis developed till 30% and 100% of failure load, for the situation of pinned-pinned beams. From the respective analysis it is possible to conclude that the former one presents the results which best fit the experimental curve, being, such values, the ones considered in the following probabilistic analysis. The obtained failure mode, for this situation, is the bending, one, which is in agreement with obtained experimental results (Figure 14).

It is important to mention that, usually, backanalysis procedures are developed till loads which are in the region of 30% of failure load. This is due to the fact that in several situations, and with the main objective of characterizing the structural behavior, the structure is submitted to an evaluation test with applied loads within this region. These loads usually correspond to a service limit state. However, in this situation, and according to Figure 13, the backanalysis process becomes more difficult to realize, as there is no information about the structural response for higher loads.

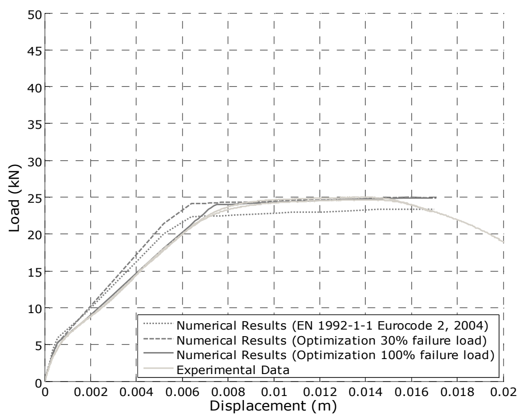

Figure 13: Numerical results

Figure 14: Failure mechanism

Table 1 presents the fitness function results considering the behavior till failure load. The backanalysis gives an improvement of 84.76% which is excellent. The same table present the values of experimental and numerical failure load, by considering parameter values from EN 1992-1-1 (2004) and from backanalysis. This former one presents an error, when compared to experimental failure load, less than 1%.

Table 1: Fitness function and failure load values

Numerical model	Fitness function		Failure load	
	Value	Improvement (%)	Value (kN)	Error (%)
EN 1992-1-1 (2004)	383.02	-	23.37	5.79
Backanalysis	58.39	84.76	24.88	0.32
Experimental data	-	-	24.80	-

Figure 15 and 16 presents measured data, and numerical results obtained by considering the values from EN 1992-1-1 (2004), and the ones from backanalysis till 30% and 100% of failure load. From the analysis it is possible to conclude that the former one presents the numerical curve which best fits the experimental one being, those values, the ones considered in the following probabilistic analysis. The cracking pattern and deformation shape of the fixed-pinned beam, in this situation, is identical to the one from experimental tests (Figure 17). Also the backanalysis, developed till 30% of failure load, presents very good results for lower loads but, for higher loads, numerical and experimental responses get far from each other. This is similar to what happens for pinned-pinned beams, and reveals the necessity of collecting more data, when in the absence of measured structural responses for higher loads.

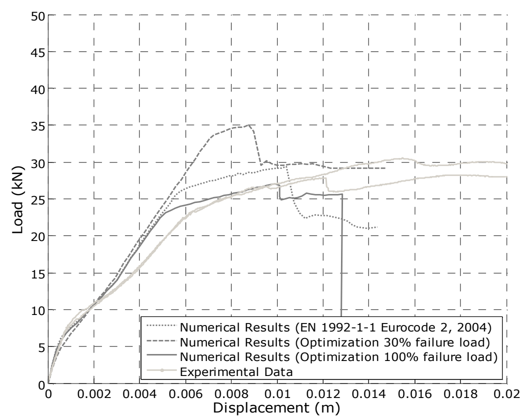

Figure 15: Numerical results

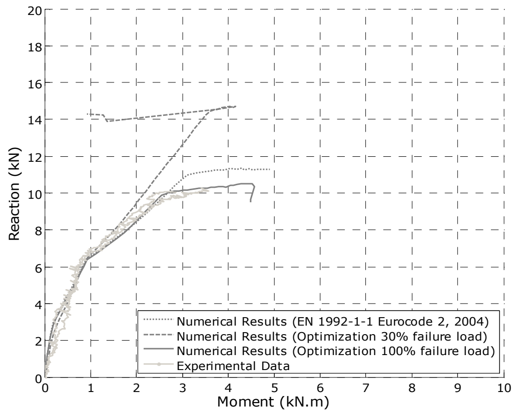

Figure 16: Numerical results

Figure 17: Failure mechanism

Table 2 and 3 presents the fitness function results considering the behavior till failure load. The improvement due to backanalysis process is of 56.67% which is really good. The same table gives experimental and numerical values for failure load and for bending moment at fixed support by considering the values from EN 1992-1-1 (2004) and the ones from backanalysis. The error, obtained from both numerical analyses, can be considered as admissible. The results from the application of optimization algorithm are very good and will serve to validate it.

Table 2: Fitness function values

Numerical model	Fitness function	
	Value	Improvement (%)
EN 1992-1-1 (2004)	752.62	-
Backanalysis	326.13	56.67
Experimental data	-	-

Table 3: Failure load and bending moment values

Numerical model	Failure load		Bending moment	
	Value (kN)	Error (%)	Value (kN.m)	Error (%)
EN 1992-1-1 (2004)	29.35	0.13	5.12	25.78
Backanalysis	27.04	8.00	4.91	28.87
Experimental data	29.39	-	6.90	-

Probabilistic analysis

Before performing any probabilistic analysis, it is necessary to assume for each critical parameter a random distribution. The respective mean is the value obtained from previous backanalysis procedure, while, the standard deviation is adopted in accordance to the bibliography (Choi et al. 2004, JCSS 2008, and Matos 2008). It is so assumed, for this situation, that there is no additional collected data, and, consequently, it is not possible to update, by using inference procedures, the previous developed numerical model. The methodology finishes so with the probabilistic analysis. There are several authors that used probabilistic analysis in civil engineering field like Ditlevsen and Madsen (1996), Nowak and Collins (2000), Pukl et al. (2006) and Teigen et al. (1991a, 1991b).

The non linear probabilistic analysis takes into consideration the critical parameters randomness. Each parameter is defined by a random distribution function according to existent bibliography (Choi et al. 2004, JCSS 2008, and Matos 2008). A correlation matrix, which relates some of those variables, is also defined. For pinned-pinned beams, the considered critical parameters distributions are present in Table 4, 5 and 6, and the correlation coefficients in Table 7 and 8.

A framework, designated by FReET, was then used to develop the probabilistic analysis (Novák et al. 2003). The FReET is based in a Latin Hypercube sampling process. A specific platform, SARA, which connects both FReET and ATENA environments, is adequately used. It was generated, and posterior analyzed, more than one hundred samples of previous developed finite element model. The numerical probabilistic distribution, obtained for each output parameter, was then compared with a random distribution attributed to the respective measured data. This consistent comparison is based on the degree of approximation between numerical and experimental confidence intervals.

Table 4: Concrete material

Parameters		Distribution	Average value	COV
Elasticity modulus [GPa]	E_c	Norm.	30.00	0.10
Compression strength [MPa]	f_c	Norm.	28.00	0.10
Tensile strength [MPa]	f_t	Norm.	1.50	0.20
Fracture energy [N/m]	G_f	Norm.	51.40	0.10

Table 5: Longitudinal reinforcement

Parameters		Distribution	Average value	COV
Yield strength [MPa]	σ_y	Norm.	540.00	0.05
Limit strength [MPa]	σ_t	Norm.	600.00	0.05
Limit strain [-]	ε_{lim}	Norm.	0.08	0.15

Table 6: Geometric parameters

Parameters	Distribution	Average value	Standard Deviation
Concrete cover [mm]	Norm.	10.00	5.00
Thickness [mm]	Norm.	75.00	3.75

Table 7: Correlation matrix (concrete)

	E_c	f_c	f_t	G_f
E_c	1.0	0.9	0.7	0.5
f_c	0.9	1.0	0.8	0.6
f_t	0.7	0.8	1.0	0.9
G_f	0.5	0.6	0.9	1.0

Table 8: Correlation matrix (reinforcing steel)

	σ_y	σ_t	ε_{lim}
σ_y	1.0	0.8	0.8
σ_t	0.8	1.0	1.0
ε_{lim}	0.8	1.0	1.0

Consequently, it is possible to determine the correspondent numerical and experimental confidence intervals. Accordingly, and assuming a Normal distribution, the confidence interval [μ-3σ; μ+3σ] (μ - average value and σ - standard deviation) that covers 99% of possibilities, is identified. A comparison between such intervals is finally developed (Figure 18).

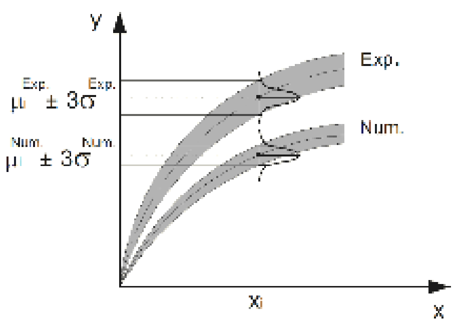

Figure 18: Probabilistic analysis

Figure 19 presents the respective comparison results for pinned-pinned beams. By analyzing Figure 19, it is possible to conclude that experimental results are within the range of possibilities, defined by numerical confidence intervals.

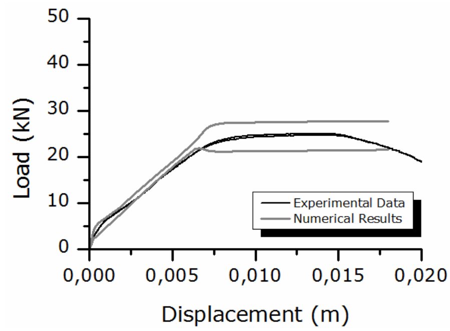

Figure 19: Experimental vs. Numerical results

A comparison between failure loads is also developed. The numerical and experimental failure loads random distributions, considered to be Normal, are first determined. Further, it is also necessary to establish a limit function (Z), which relates the proximity between both random distributions (Figure 20). An approximation index (β) is then used:

$$\beta = \left(\mu_{Exp.} - \mu_{Num.} \right) / \left(\sigma_{Exp.}{}^2 + \sigma_{Num.}{}^2 \right)^{1/2} \qquad (4)$$

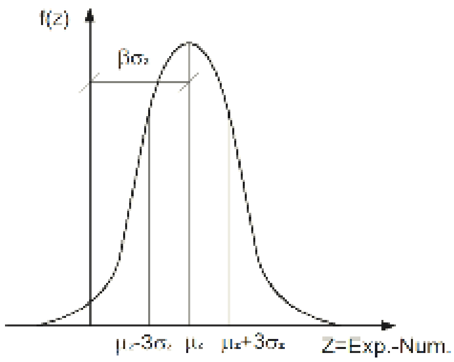

Figure 20: Approximation index (β)

where μ_{Exp}, μ_{Num}, σ_{Exp} and σ_{Num} are, respectively, the experimental and numerical random distributions mean and standard deviation. Table 9 presents the main results for pinned-pinned beams in which expression (4) is used to determine the approximation index (β). From the respective analysis, it is possible to conclude that this index presents a lower value, which means that the approximation between both random distributions is higher (Matos et al., 2010).

Table 9: Comparison of failure load (kN)

Distribution law	Experimental failure load		Numerical failure load		Approximation index (β)
	Average value	Standard deviation	Average value	Standard deviation	
Norm.	24.80	0.25	24.57	1.03	0.22

The same way, for fixed-pinned beams, it was also developed a non linear probabilistic analysis. In this analysis it was assumed a random distribution for each critical parameter, according to existent bibliography (JCSS, 2001, Choi et al., 2004, and Matos, 2008). The random distribution mean value is the one determined from previous backanalysis. It was also defined the correlation matrixes, which relate such variables. The respective distribution parameters and correlation coefficients are present from Table 10 to 15. The FReET framework was used again to develop the probabilistic analysis (Novák et al. 2003). The obtained results were then analyzed. Such analysis consisted in determining the numerical and experimental confidence intervals, which corresponds to 99% of possibilities. A comparison between such intervals was then performed.

By analyzing Figures 21 and 22, it is possible to conclude that experimental results are within the possibility defined by numerical confidence intervals. A comparison between numerical and experimental results, of two output variables, respectively, failure load and bending moment at fixed support, was also performed. In order to do that, it was defined a limit function (Z), which relates the proximity between both numerical and experimental random distributions, and an approximation index (β) determined (Figure 20). From the analysis of Table 16, it is possible to conclude that both variables present a low approximation index value, which let us conclude about the proximity between numerical and experimental data.

Table 10: Concrete material

Parameters		Distribution	Average value	COV
Elasticity modulus [GPa]	E_c	Norm.	28.01	0.10
Compression strength [MPa]	f_c	Norm.	30.77	0.10
Tensile strength [MPa]	f_t	Norm.	2.67	0.20
Fracture energy [N/m]	G_f	Norm.	103.91	0.10

Table 11: Longitudinal reinforcement

Parameters		Distribution	Average value	COV
Yield strength [MPa]	σ_y	Norm.	542.30	0.10
Limit strength [MPa]	σ_t	Norm.	655.64	0.10
Limit strain [-]	ε_{lim}	Norm.	0.12	0.20

Table 12: Geometric parameters

Parameters	Distribution	Average value	Standard Deviation
Superior concrete cover [mm]	Norm.	25.84	10.00
Inferior concrete cover [mm]	Norm.	22.34	5.00
Thickness [mm]	Norm.	75.00	3.75

Table 13: Other parameters

Parameters	Distribution	Average value	COV
Constant spring [kN/m]	Norm.	200.00	0.10

Table 14: Correlation matrix (concrete)

	E_c	f_c	f_t	G_f
E_c	1.0	0.9	0.7	0.5
f_c	0.9	1.0	0.8	0.6
f_t	0.7	0.8	1.0	0.9
G_f	0.5	0.6	0.9	1.0

Table 15: Correlation matrix (reinforcing steel)

	σ_y	σ_t	ε_{lim}
σ_y	1.0	0.8	0.8
σ_t	0.8	1.0	1.0
ε_{lim}	0.8	1.0	1.0

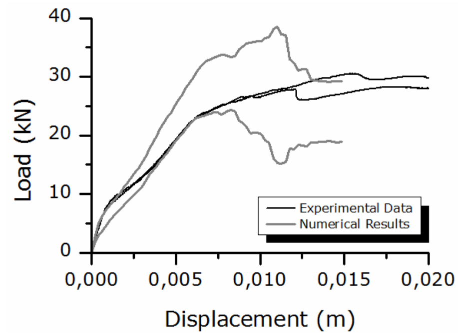

Figure 21: Experimental vs. Numerical results

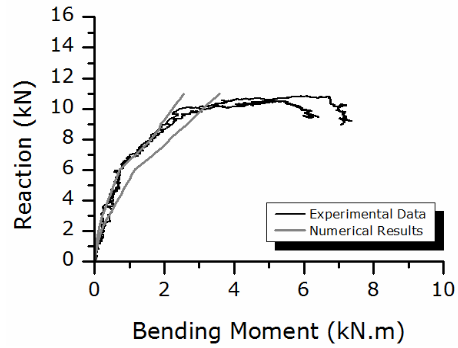

Figure 22: Experimental vs. Numerical results

Table 16: Comparison of failure load (kN) and bending moment (kN.m)

Parameter	Distribution law	Experimental data		Numerical results		Approximation index (β)
		Average value	Standard deviation	Average value	Standard deviation	
Failure load	Norm.	29.39	1.59	30.01	1.92	0.25
Bending moment	Norm.	6.90	0.67	4.35	1.86	1.29

CONCLUSIONS AND FURTHER RESEARCH

This paper describes a methodology for the consistent evaluation of the behavior of any structure by taking, into consideration, all uncertainty sources. Such methodology contains both backanalysis and inference procedures. The inference process is based in a Bayesian framework. The backanalysis consists in fitting the numerical curve to the experimental one. This optimization procedure is defined as structural identification (St-Id).

Within this paper, a St-Id technique based in a genetic algorithm framework, which considers the uncertainty present both in numerical and in experimental data, is proposed. The algorithm is tested with two batches of reinforced concrete beams which were loaded up to failure in laboratory. It reveals an improvement in the approximation between numerical and experimental results, taking, as a reference, the numerical results obtained by using the parameters from EN 1992-1-1 (2004). However, the related computational costs are high and other optimization algorithms should be further studied. On majority of situations, when evaluating the behavior of real structures, a load test is developed. However, during these tests, the applied load usually presents an intensity equivalent to 30% of the failure load. In order to validate the methodology, the proposed St-Id technique is applied in two different situations, one, by studying the beams behavior till failure and, one other, till 30% of failure load.
The results obtained from the application of the St-Id technique validated it. They are very good when this technique is applied to a load equivalent to the failure one. However, in situations of low intensity loads, we may have different set of values for critical parameters that fit, very well, the obtained experimental curves till a load of such an intensity, but, when extrapolating the results for higher loads, the structural behavior may completely change. We may even get experimental failure loads lower than the numerical ones, which leads to unsafe previsions. It is so very important to accomplish the results from St-Id with other information from Non Destructive Tests, visual inspection and engineering judgment. Part of developed methodology, respectively backanalysis T1 and the full probabilistic analysis, were already tested with success. However, there is some research that must be further developed. It is necessary to choose the most suitable optimization algorithm for backanalysis procedures, and the implementation of backanalysis T2. The developed method was only applied with a set of reinforced concrete beams, tested at laboratory. It is proposed to apply it with a real structure.

This methodology constitutes an excellent support for any decision, before, during and after any event hazard, during the whole infrastructure life-cycle. Within the society perspective, the optimal decision is the one that maximizes the respective utility of the existent infrastructure network, during the largest period of time and, at same time, with the lowest related costs. Such decisions, if right, will improve the quality of life of future generations.

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