Reliability analysis of a historical bridge against ship impact with ANSYS optiSLang

Roger Schlegel[1], Tino Dannenberg[1], Marco Grosse[1], Thomas Most[1]

Claus Kunz[2]

[1)]Dynardo GmbH, Weimar, Germany

[2)] Bundesanstalt für Wasserbau, Karlsruhe, Germany

Summary

Ship impact against bridges crossing waterways may damage the structure and in some unlikely case may cause a failure with dramatical consequences. The contribution shows a practical example for determining the failure probability of a historical bridge against ship impact. For this purpose, a parametric, automatized workflow was generated with ANSYS optiSLang using a nonlinear dynamic finiteelement analysis of a 3 dimensional bridge model. In the ANSYS FE-model nonlinear material models for concrete, historical masonry and the soil have been considered. The applied calculation method allowed a realistic calculation of the bridge by utilizing the available reserves of the load bearing capacity due to cracking and due to the load redistributions in the structure.
In preparation of the probabilistic assessment of the bridge ultimate load calculations have been applied to identify the critical impact scenario, the failure mechanism and the ultimate load capacity of the bridge. Based on these results, different damage criteria had been derived, which are considered in a first variation and sensitivity analysis for the decisive impact scenario. With this sensitivity evaluation the most relevant parameters for the load behavior and for the evaluation criteria had been identified and only a small number of important input parameters could be identified.
In the following reliability analysis the most suitable evaluation criterion was used to estimate the failure probability. The estimate was validated by using two different types of reliability analysis techniques within an automated workflow, an Adaptive Response Surface Approach in the significant parameter subspace and a Global Response Surface in the full parameter space combined with directional sampling.
With the presented strategy a confident estimate of the failure probability could be achieved and the safety of the historical bridge against ship impact could be proven.

Keywords

Berstschutz, Rotations-Prüfstände, Impaktanalyse, ANSYS-LSDYNA, optiSLang

1. Robustness Evaluation

Satisfying design requirements will necessitate ensuring that the scatter of all important responses by fluctuating geometrical, material or environmental variability lies within acceptable design limits. With the help of the robustness analysis this scatter can be estimated. Within this framework, the scatter of a response may be described by its mean value and standard deviation or its safety margin with respect to a specified failure limit. The safety margin can be variance-based (specifying a margin between failure and the mean value) or probability-based (using the probability that the failure limit is exceeded). In Figure 1 this is shown in principle.

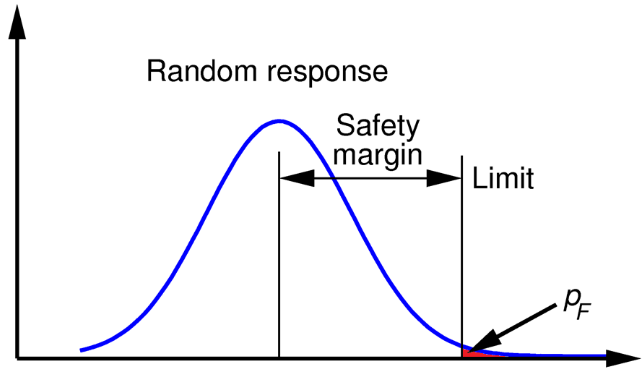

Figure 1: Scatter of a fluctuating response with safety margin (distance between mean and the failure limit) and the corresponding probability of failure p_F

In the variance-based approach the safety margin is often given in terms of the corresponding standard deviation of the corresponding response. A “six sigma” design should fulfil a safety margin of six times the standard deviation. Assuming a normally distributed response, the classical six sigma concept considers an additional safety margin of 1.5 times the standard deviation. The 4.5 sigma margin of a normal distribution corresponds to a failure rate of 3.4 defects out of one million design realizations. The assumption of a normally distributed response may be not invalid if non-linear effects dominate the mechanisms of failure as discussed in [8] and [13]. In such cases the extrapolation of rare event probabilities like 3.4 out of a million just from the estimated mean value and standard deviation may be strongly erroneous. Thus, the assumption of a normal distribution should be verified or the probability of failure should be estimated with more qualified reliability methods.
For industrial applications with a larger number of scattering inputs and non-linear dependencies Monte Carlo based methods are often suitable [12]. The Latin Hypercube Sampling (LHS) is one approach, where the distribution of the samples is optimized with respect to small errors in the statistical estimates of the input scatter. This method does not assume any degree of model behaviour and can handle also discontinuous responses. Furthermore, it works independently of the number of input parameters. Rough estimates of mean and standard deviation are possible with just 20 solver runs. More precise estimates of mean and standard deviation can be obtained by using 50 to 100 samples, but of course such a pure sampling strategies need a very high number of samples for a reliable estimations or rare event probabilities with six-sigma accuracy. Based on the evaluated data and the estimated scatter of the responses, variance-based sensitivity measures can be evaluated in order to further analyse the source of uncertainty. From our experience using a small LHS sample set to estimate standard deviation is an effective method which is also robust to system nonlinearity. By fitting the distribution function into the histogram of the response we also can verify the window of probability based on standard deviation as well as on fitted distribution functions.

2. Reliability Analysis

With the reliability method the probability of reaching a failure limit is obtained by an integration of the probability density of the uncertainties in the failure domain as shown in Figure 2. One well-known method is the Monte Carlo Simulation [9], which can be applied independently of the model non-linearity and the number of input parameters. This method is very robust and can detect several failure regions with highly non-linear dependencies. Unfortunately, it requires an extremely large number of solver runs to proof rare events. Therefore, more advanced sampling strategies have been developed like Directional Sampling, where the domain of input variables is scanned by a line search in different directions, or Importance Sampling, where the sampling density is adapted in order to cover the failure domain sufficiently and to obtain more accurate probability estimates with much less solver calls.

Other methods like the First or Second Order Reliability Method (FORM & SORM) are still more efficient than the sampling methods by approximating the boundary between the safe and the failure domain, the so-called limit state. In contrast to a global low order approximation of the whole response, the approximation of the limit state around the most probable failure point (MPP) is much more accurate. Nevertheless, only one dominant failure point can be found and evaluated. This limitation holds even for the Importance Sampling Procedure Using Design points (ISPUD), where the non-linearity of the limit state can be considered by a sampling around the MPP. A good overview of these “classical” methods is given in Bucher [2].

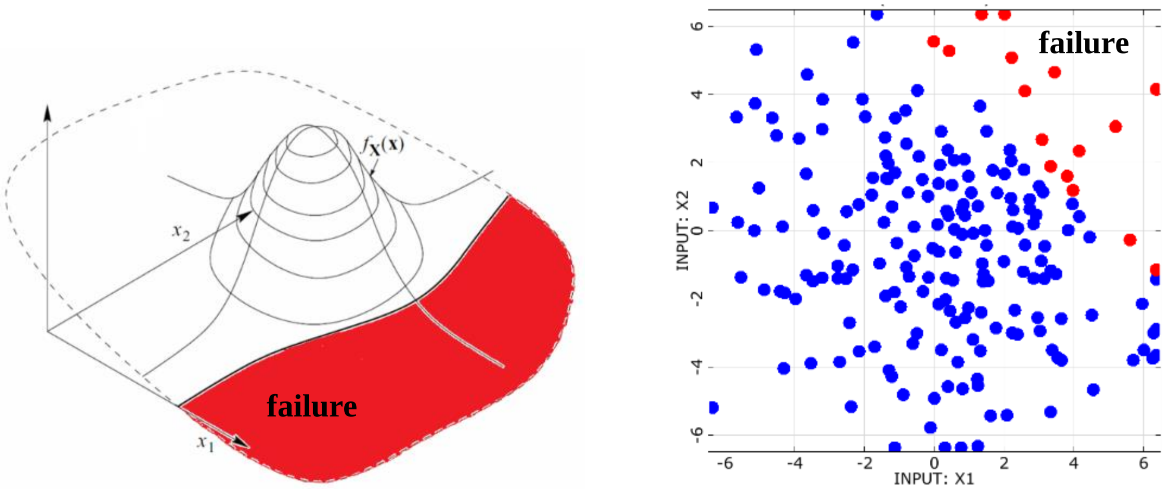

Figure 2: Reliability analysis as multi-dimensional integration of the probability density of the inputs uncertainties over the failure domain (left) and integration by Monte Carlo Simulation (right)

For a successful application of global response surface methods, it is necessary to assure that the region around the most probable failure point is approximated with sufficient accuracy. This can be reached by an iterative adaptation scheme, where new support points are generated in this region. With this improvement also two or three important failure regions can be represented with a small number of solver runs as shown in Roos & Adam [10].
In reliability analysis where small event probabilities have to be estimated, we have to pay special attention that the algorithms obtain an acceptable level of confidence in order to detect the important regions of failure. Otherwise, they may estimate a much smaller failure probability and the safety assessment will be much too optimistic. The available methods for an efficient reliability analysis try to learn where the dominant failure regions are and concentrate their simulation effort in those regions in order to drastically reduce the necessary CAE simulations. This is necessary to become candidates of reliability for real world applications. Of course there is always a risk that experimenting with such approaches will lead to inappropriate short cuts, perhaps missing the failure domain and providing too optimistic an estimation of failure probability. Therefore, we strongly recommend that at least two different reliability methods are used to verify variance-based estimates of the failure probability in order to make reasonable design decisions based on CAE-models.

3. Reliability Analysis of the Main Bridge in Lohr am Main

In this project the old Main-bridge in Lohr am Main was analyzed. The bridge consists of 5 piers and 6 arches. 3 arches span the river and 2 piers are founded on the river ground as shown in Figure 3. The bridge was built between 1873 and 1875 with sandstone masonry. The simulations are carried out on the complete 3D model of the bridge considering the current rehabilitated state of the construction (e.g. including tensile bars) and the foundation (sheet pile reinforcements).

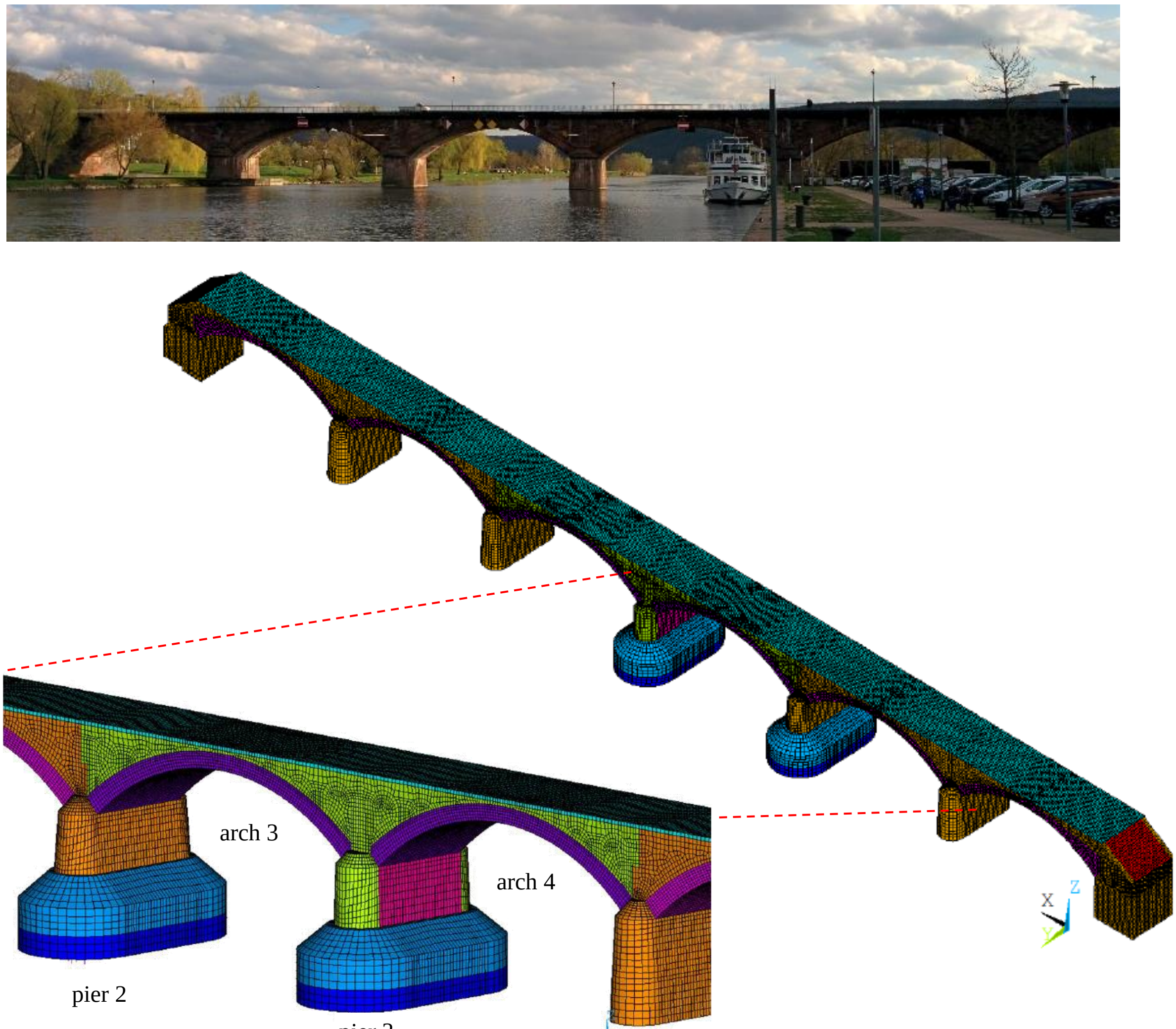

Figure 3: View on the bridge in Lohr am Main
and corresponding finite element model using ANSYS Mechanical

First in a deterministic analysis five quasi-static load cases have been analyzed: front, edge and arch impacts due to ships acting on the water piers. By means of these analyses the dominant load case, the expected failure modes and possible failure criteria should be investigated. As a result of these simulations using a finite element model with ANSYS Mechanical [1], the front impact on pier number 2 was found to be most dominant. The plastic behavior of the masonry, concrete and soil due to cracking and shear sliding was modelled using the material library ANSYS multiPlas [4], [11].
In Figure 4 the deformations are shown for this dominant load case. For a maximum deformation of 12.7 mm, the final failure of the pier occurred. This load case was considered in the probabilistic analyses. As failure criteria different response values such as deformations, stresses, external forces and the gradients of the plastic region and plastic work have been investigated within a variance-based sensitivity analysis. As input uncertainties 60 random parameters have been considered: the elastic and plastic material parameters were assumed to be log-normally distributed while the geometry parameters were taken as normal. The material characterization and its scattering is based on extensive measuring by the Federal Institute for Hydraulic Engineering on the structure as well as data taken from literature [5]. The impact load was assumed to be time-dependent with a random scalar scaling factor (Figure 5) and a random position, where the impact load was acting on the structure. The scatter of the load amplitude was considered as a lognormal distribution with a spread of 74%. For the load position, a truncated normal distribution with a spread of 30% was assumed.

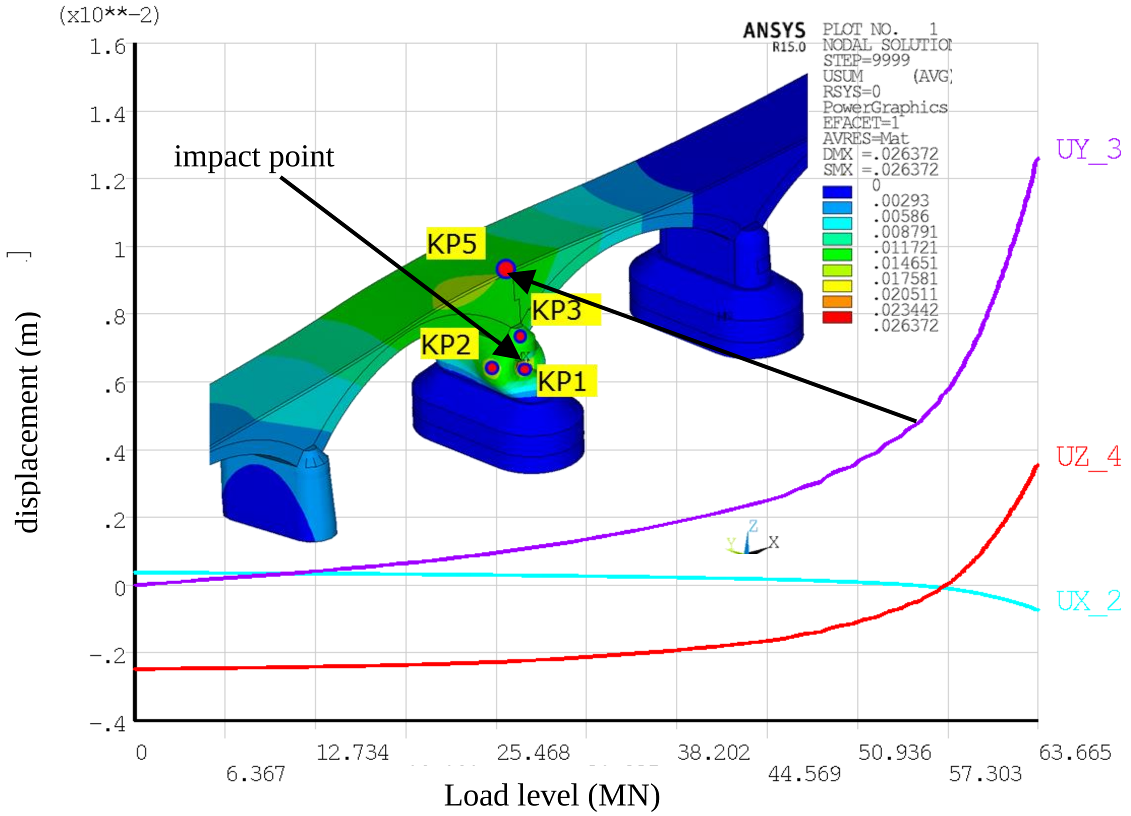

Figure 4: Maximum deformations depending on the impact load amplitude

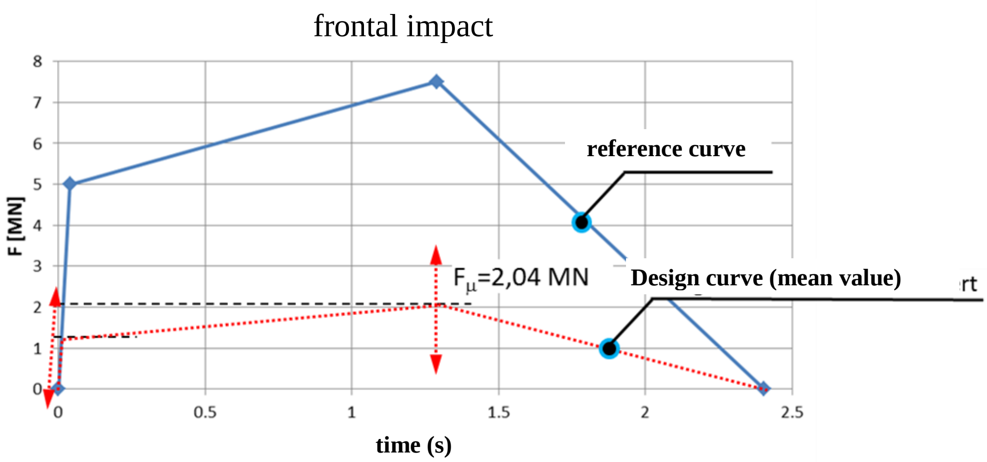

Figure 5: Time depending impact load acting on the pier scaled with a random factor

With help of 191 Latin Hypercube samples, which reproduced the assumed scatter of the input parameters very well, the scatter of the dynamic response could be investigated. In Figure 6 the displacements over time are shown for the individual samples. By using the Metamodel of Optimal Prognosis [6], [7] the contribution of the input uncertainty could be quantified. As shown additionally in Figure 6 only six parameters out of the 60 inputs could explain the variance of the maximum deformation with about 97%. Most dominant are the impact amplitude L_Amp, position L_Pos and the Young's modulus in the pier.

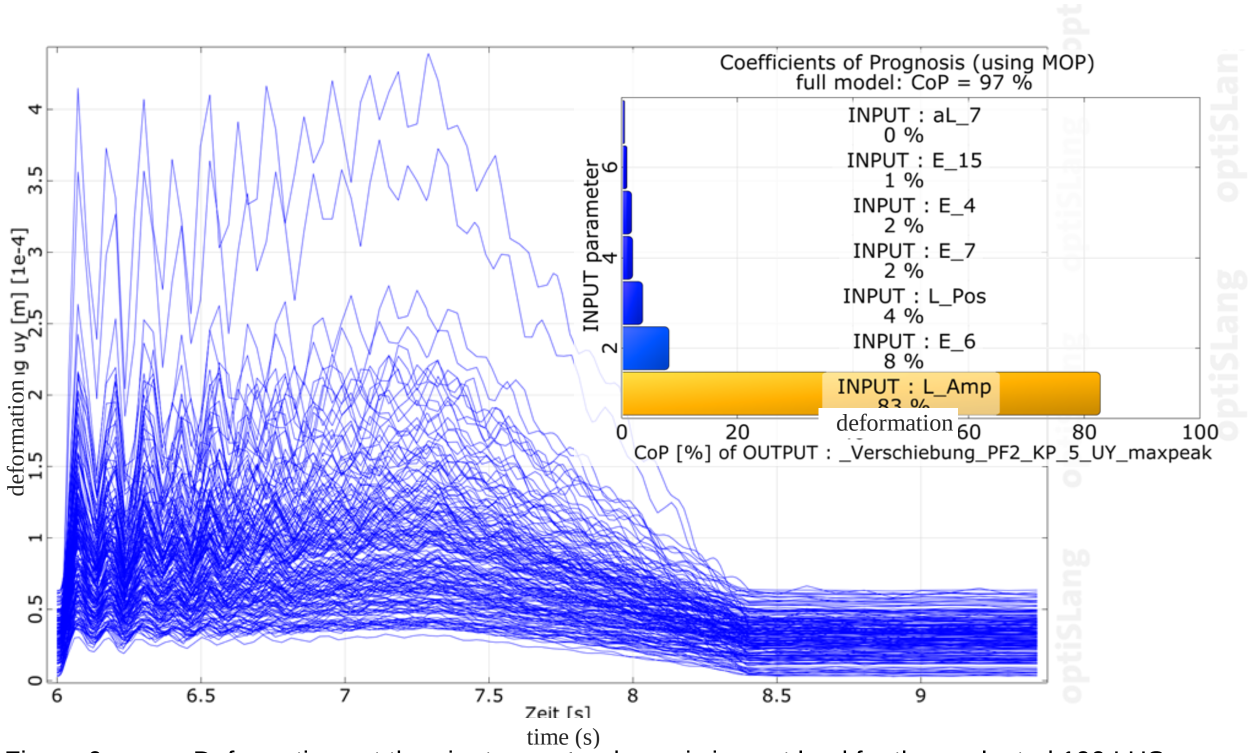

Figure 6: Deformations at the pier top under dynamic impact load for the evaluated 190 LHS samples and corresponding sensitivities of the input parameters w.r.t. the maximum deformation

Based on the variation the maximum displacements the safety margin could be estimated. By considering failure if the maximum deformation exceeds 12.7 mm, which was obtained from the dominant failure load case, the safety margin was about 220 times the standard deviation. For such a huge safety margin a qualified reliability analysis was not possible, since the necessary transformation of the joint probability density function from the original to the standard-Gaussian space and vice versa could not be evaluated numerically.

Therefore, a different strategy was performed in order to proof the reliability of the structure. Instead of estimating the failure probability for the maximum deformation limit, the maximum possible deformations for the required safety level was estimated. As safety requirement the risk class 2 according the Eurocode [3] was given, which corresponds to a failure probability of 10^{-6} or equivalently to a reliability index of 4.75.

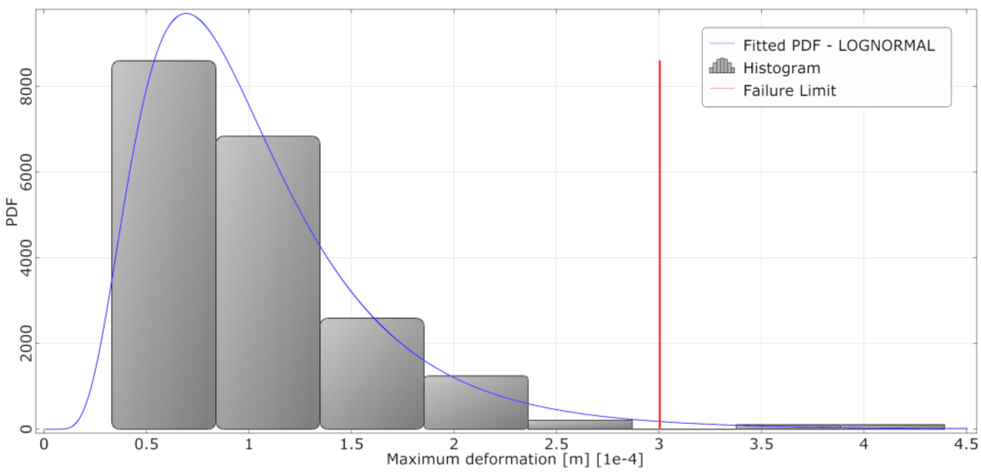

Figure 7: Variation of the maximum deformation observed from 191 LHS samples with fitted log-normal distribution and failure limit of 0,3 mm

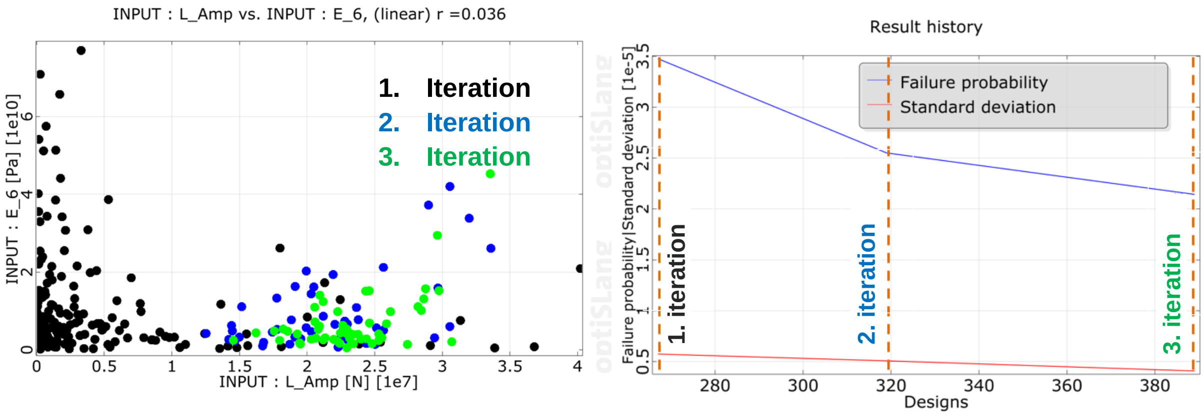

Figure 8: Adaptive Response Surface Method: adaptation in the subspace of most relevant parameters (left) and convergence of the estimated failure probability (right) for the failure limit of 1,2 mm

For this procedure the following steps have been performed:

1. From the LHS sampling the relative probability could be estimated for small sigma levels by using the best fit distribution of the maximum deformation, which was log-normal as shown in Figure 7.
2. For an estimated failure limit of 1,2 mm a qualified reliability analysis was performed using an Adaptive Response Surface Method combined with directional sampling within 3 adaptation steps as shown in Figure 8. For this procedure only the six most relevant input parameters have been considered.
3. Re-using the ARSM designs a global response surface using the MOP was generated and a directional sampling was performed on the MOP approximation.
4. The ARSM approach was applied again for a failure limit of 2,0 mm.
5. All designs of the step 2 and 4 have been re-used to generate a MOP and apply Directional sampling on the approximation model.
6. The failure limit corresponding to a failure probability of 10^{-6} and the failure probability of the deterministic failure criteria were obtained by using a linear regression w.r.t. the estimated reliability indices as shown in Figure 9.

An overview of the reliability estimates in given in table 1: based on the available 191 LHS samples a distribution fitting and reliability estimate was possible for a failure probability larger than 10^{-2}. By using the Adaptive Response Surface Method a qualified reliability estimate could be obtained for a failure limit of 1,2 mm by 389 further model evaluations. A further analyses by ARSM with 328 model evaluations was performed by considering a maximum deformation of 2,0 mm in order to cover even smaller values of the failure probability. Since the failure probability for this limit was still larger than 10^{-6}, the samples of both analyses were used to build a global MOP and estimating the failure probability corresponding to a maximum deformation of 3,0 mm.

In the presented iterative procedure the failure limit w.r.t. the dominant load case was found for a given target failure probability. With help a 3D finite element analysis considering nonlinear material behaviour the maximum load capacity of the bridge was calculated. Since the estimated failure limit is much smaller than the load capacity, the required safety level of the bridge could be proven. For further details of the simulation model the interested reader is referred to [5] or to a direct communication with the Dynardo GmbH or the Federal Institute for Hydraulic Engineering in Karlsruhe.

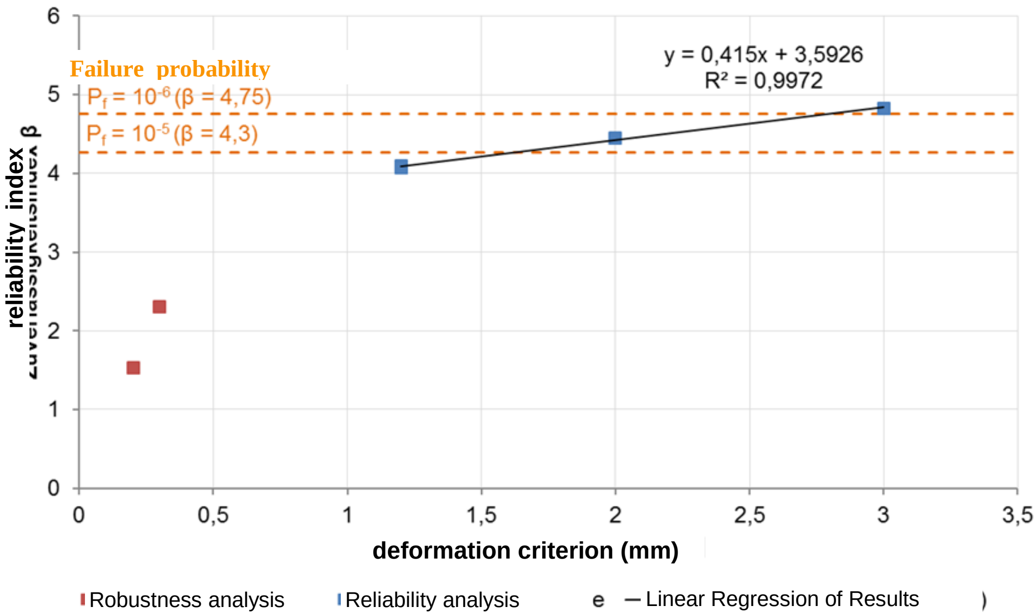

Figure 9: Reliability index for the different reliability estimates depending on the failure criteria including interpolation for a failure probability of 10^{-5} and 10^{-6}

Limit state = maximum deformation	**Failure probability**	**Reliability index β**	**Number of simulation runs**
0,2 mm	$6{,}28 \cdot 10^{-2}$ (LHS)	1,53	- (re-use of 191)
0,3mm	$1{,}05 \cdot 10^{-2}$ (LHS)	2,31	- (re-use of 191)
1,2 mm	$2{,}14 \cdot 10^{-5}$ (ARSM-DS) $2{,}30 \cdot 10^{-5}$ (MOP-DS)	4,09 4,08	389 - (re-use of 389)
1,7 mm	$1{,}0 \cdot 10^{-5}$	4,3	interpolated
2,0 mm	$4{,}32 \cdot 10^{-6}$ (ARSM-DS)	4,45	328
2,8 mm	$1{,}0 \cdot 10^{-6}$	4,75	interpolated
3,0 mm	$6{,}96 \cdot 10^{-7}$ (MOP-DS)	4,83	- (re-use of 389+328)
12,7 mm	$4{,}0 \cdot 10^{-19}$	8,86	extrapolated

Table. 1: Overview of reliability estimates for the different analysis steps

4. References

[1] ANSYS Users Manual for ANSYS Rev. 15.07, Analysis Guides, ANSYS Inc., Houston, Canonsburg, 2015

[2] Bucher, C. (2009). Computational Analysis of Randomness in Structural Mechanics. London: CRC Press, Taylor & Francis Group.

[3] DIN EN 1990 Eurocode: Grundlagen der Tragwerksplanung; Deutsche Fassung EN 1990:2002

[4] multiPlas – elastoplastic material models for ANSYS, Release 5.3.1, DYNARDO GmbH, Weimar, www.dynardo.de multiPlas user's manual, 2016

[5] Dynardo. K15-BAW-04, Technical report (unpublished). DYNARDO GmbH, Weimar, www.dynardo.de, 2016

[6] Dynardo GmbH (2017). Methods for multi-disciplinary optimization and robustness analysis – optiSLang 6.1 documentation

[7] Most, T. and J.Will (2008). Metamodel of Optimal Prognosis - an automatic approach for variable reduction and optimal metamodel selection, Proceedings Weimarer Optimization and Stochastic Days 5.0, Weimar, Germany

[8] Most, T. and J. Will (2012). Robust Design Optimization in industrial virtual product development, Proceedings 5th International Conference on Reliable Engineering Computing, Brno, 2012

[9] Rubinstein, R. Y. (1981). Simulation and the Monte Carlo Method. New York: John Wiley & Sons.

[10] Roos, D., U. Adam (2006). Adaptive Moving Least Squares approximation for the design reliability analysis. Proceedings Weimarer Optimization and Stochastic Days 3.0, Weimar, Germany

[11] Schlegel, R.: Numerische Berechnung von Mauerwerkstrukturen in homogenen und diskreten Modellierungsstrategien. Dissertation, Bauhaus-Universität Weimar (2004)

[12] Will, J.(2007) : State of the Art – robustness in CAE-based virtual prototyping processes of automotive applications, Proceedings Weimarer Optimierungs- und Stochastiktage 4.0, www.dynardo.de

[13] Will, J., T. Most and S. Kunath (2017) Robust Design Optimization in Virtual Product Development, NAFEMS Ltd., to appear