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SHM BASED SYSTEM DESIGN OF A WIND TURBINE TOWER USING A MODAL SENSITIVITY BASED BAYES DETECTOR

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ABSTRACT

It is investigated if material based structural safety can be replaced with safety obtained from SHM. SHM on its own does not add any value to a structure unless there is a decision policy attached. The further attachment of a loss function enables upfront calculation of the expected utility. In the presented case, damage sensitive features from sensitivity based damage detection are used in a supervised learning and optimization scheme. A Bayes detector, i.e. the static decision rule that minimizes the expected utility, is utilized for the system design. The technique is demonstrated in a simulation case of the NREL 5MW wind turbine tower subjected to bending fatigue and horizontal circumferential cracking at weld locations. Decision driven SHM is shown to change the initial design safety of the structure in the fatigue limit state. A common optimum of material safety and classifier threshold is found, enabling the calculation of the expected value of SHM. A sensitivity analysis of the feature extraction and of the loss function is included.

KEYWORDS : *SHM system design, Bayesian experimental design, Detection Theory, Damage detection, Statistical Pattern Recognition*

INTRODUCTION

For SHM to become feasible in the building sector, the expected value of SHM must be shown. There are multiple threats against the future of embedded SHM in civil structures, three of which are listed below:

- In the general perception, civil structures are safe enough already and SHM adds no actual value. The expected value must be proven, upfront.
- Initial costs are likely to supersede the expected life cycle costs as the design driver.
- The risk-willingness is small. This is a real problem as the benefit from SHM can only be achieved if the owner accepts the unknown probability of SHM malfunction.

These threats make it difficult to find industrial partners for real world application and they force the direction of search against overcoming these treats. The present work deals with overcoming the first item on the list.

For a thorough literature review and background reading on SHM the authors recommend the review [1]. In the present work, the statistical pattern recognition paradigm for SHM [2] is used to treat damage detection and decision support optimization as a machine learning problem on vibration data from a structure.

1 BACKGROUND THEORY

The use of Bayesian pre-posterior decision analysis [3] in experimental design [4] enables averaging over the sample space to maximize the posterior expected utility. The expected utility of

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the best decision is given in (1). This is a terminal decision analysis as posterior expected utility is maximized.

$$\int_x \max_d \int_\theta U(d,\theta,x)p(\theta\,|\,x)p(x)d\theta dx \tag{1}$$

Where U is the utility function, x ∈ X is the data set, θ ∈ Θ is the (unknown) state and d ∈ D is the terminal decision. By including choice of experiment **z** ∈ Z in (1), Lindley finds the expected utility of the best decision set (*z,d*) to be given by (2), effectively defining a Bayesian pre-posterior decision analysis.

$$\max_z \int_x \max_d \int_\theta U(d,\theta,x,z)p(\theta\,|\,x;z)p(x\,|\,z)d\theta dx \tag{2}$$

Expression (2) is visualized by the decision tree in Figure 1.

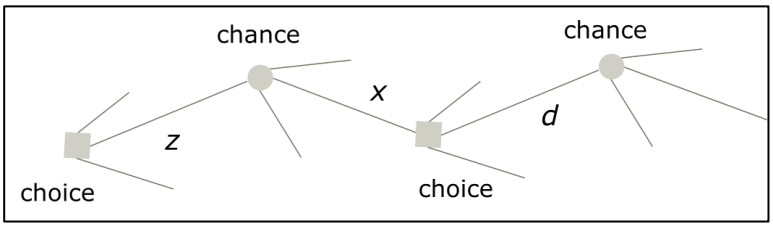

Figure 1, decision tree representing pre-posterior decision analysis of Bayesian experimental design (BED)

When the utility function reflects the purpose of the experiment, this defines the optimum design of the experiment.

Bayes risk is a loss function integrated over the posterior distribution of the state variables:

$$r(x,\pi) = \int L(\theta,\delta(x))p(\theta\,|\,x)d\theta \tag{3}$$

If benefits are neglected and a loss function is used instead of the utility function, then the expression becomes the minimization of expected loss, i.e. of Bayes risk. Flynn [5] showed that this theory could be applied for an SHM system in finding the shared optimum between system design and terminal decisions that minimize the Bayes risk. This is the basic of SHM system design.

In the basic case of a static discrete decision rule and group classification, the minimum expected loss (MEL) for a given system design is found by minimizing over sample space *X*:

$$\min_d \sum_{j,k} L^e_{j,k}(d_k,\theta_j,z)p(x\,|\,\theta_j;z) + L^i(z) \tag{4}$$

Where L^e is the extrinsic loss function corresponding to the confusion matrix and L^i is the loss function associated with system costs. A detector T transforms feature statistics $p(x|\theta_j,z)$ into discrete decisions $P(d_k|\theta_j,z)$. An optimal detector is found by minimizing Bayes loss.

Combining the Bayesian pre-posterior decision analysis of expression (2) with optimal detector design in expression (4) we find that minimizing over *Z* space leads to Bayesian system design:

$$\min_{z,d} \sum_{j,k} L^e_{j,k}(d_k,\theta_j,z)P(d_k\,|\,\theta_j;z)P(\theta_j) + L^i(z) \tag{5}$$

Here **z** ∈ Z represents system variables, e.g. choice of design variables, choice of experiments, choice of inspections, etc. By setting an appropriate utility function U, optimization of the decisions (**z**, **d**) yields the risk-optimal design.

The classifier statistics can be calculated directly if closed form distributions for the features $p(x|\theta_j)$ are known. If they are not available, which is often the case; the statistics can be estimated by sampling.

In the case of a time varying problem, the sum is taken over time, in which case all probabilities become conditional on the event-probabilities up until the current time step t_l:

$$\min_{z,d} \sum_{j,k,l} L^e_{j,k}(d_k, \theta_j, z) P(d_k \mid \theta_j; z) P(\theta_j \mid t_l) + L^i(z) \tag{6}$$

This will yield the pre-posterior optimal design of experiments based on a static terminal decision policy.

In the case of inequality events (i.e. no sized events), the updated probabilities are calculated as conditional probabilities, using Bayesian updating. The approach is well known from risk based inspection (RBI) analysis, as described in e.g. [6] and [7].

$$P(M \le 0 \mid H \le 0) = \frac{P(M \le 0 \bigcap H \le 0)}{P(H \le 0)} \tag{7}$$

The probabilities can be cumbersome to calculate, as the number of parallel systems that must be analysed is exponentially dependent on the number of events during the structures service life. Where M is the safety margin for failure and H is the event margin of all preceding events, e.g. repairs and inspections. The probabilities can be calculated by the FORM approximation for a parallel system:

$$P_{sys} \approx \Phi(-\{\beta\}; \{0\}, \{\alpha\}^T \{\alpha\}) \tag{8}$$

In RBI, an optimal inspections plan is calculated before realizing the structure, and the plan is then updated based on inspection findings. However, in the proposed framework for SHM based design, the SHM is treated as a decision support tool. Thus an inspection plan is not made, but instead inspections are triggered by the decision rule of the detector.

2 CASE STUDY: TOWER FOR THE NREL 5MW BASELINE WIND TURBINE

In order to evaluate the effect of the vibration based SHM on the overall system costs, a wind turbine tower is considered. Only bending fatigue design for the lower section of the tower is considered. Horizontal, circumferential though-cracks propagating in pure mode-I are assumed. The structure's properties are taken from [8] and a FE model is used for simulation. Fatigue loads are estimated with aero-elastic analysis in LACflex 1.6.2 for wind class II-B and directional conditions corresponding to Danish coastal conditions at Hvide Sande and are extrapolated to a service life of 20 years. The stresses are calculated as:

$$S_i = X_s X_{aero} X_{SCF} \Delta\sigma_i \ , \quad \mathrm{i} = 1,2,...,\mathrm{k} \tag{9}$$

Where S_i is the mean stress range in stress range bin *i*, X_s is a model uncertainty to account for uncertainty on exposure (terrain), climate statistics, structural dynamics and stress evaluation. X_{aero} is a model uncertainty representing the uncertainty on the shape factor. Both model uncertainties are set in accordance with the uncertainty model used in the IEC [9].

The SN fatigue analysis is performed as a probabilistic analysis assuming a bi-linear Wöhler curve with no endurance limit and linear damage accumulation. The corresponding limit state is:

$$g = \Delta - \sum_{i=1}^{k} \frac{n_i}{N_i} \ , \quad \mathrm{N_i} = K_j (S_i)^{-m_j} \quad , \quad \mathrm{j} = \begin{Bmatrix} 1 \, if \ \mathrm{S_i} > \left(\frac{K_2}{K_1}\right)^{\frac{1}{m_2 - m_1}} \\ 2, \text{otherwise} \end{Bmatrix} \tag{10}$$

Where Δ is the Miner's damage index, n_i is the cycle count in bin i, N_i is the cycles to failure in bin i, m_j is the Wöhler exponent and K_j the Wöhler constant. The limit state equation for the LEFM model is indirectly based on the brittle fracture criterion:

$$g = a_c - a \tag{9}$$

Given the chosen nominal stress SN parameters for a wall to flange welding, the annual reliability index is minimum β=3.3, calculated with first order reliability method (FORM) and verified with crude monte carlo (CMC) simulations. This is well in accordance with Veldkamp [10] who shoved that the optimal annual reliability index for the tower given an interest rate of r=5% is β=3.3.

Table 1, variables used in the example

Variable	Type	Mean	Std
$t_{reference}$	D	0.0351	
r	D	3	
m_1	D	3	
m_2	D	5	
S, n	D		
$Log_{10}(K1)$ $Log_{10}(K2)$	N	12.564 16.106	0.2, ρ = 1 0.25
Δ	LN	1	0.3
X_S	LN	1	0.132
X_{aero}	G	1	0.1
X_{SCF}	LN	1	0.2
X_{SIF}	LN	1	0.2
a_c	D	2	
N_0	D	0	
m		ln(C) = -15.84 – 3.34m	
ln(C)	N	-25.66 (fitted)	0.77
a_0	LN	10^{-4} (fitted)	10^{-4}
r	D	5%	
C_I	D	0.040 t / $t_{reference}$ (fitted to $\beta_{ann,min}$)	
$\beta_{ann,min}$	D	3.30	

Table 2, loss function used for the example. The same function is used by Straub [11] for RBI of fatigue damage on steel structures.

	critical	non-critical
decide critical	*True positive* C_{11} = 0.01	*False positive* C_{10} = 0.001
decide non-critical	*False negative* C_{01} = 1	*True negative* C_{00} = 0

Reliability based optimization (RBSO) was used to fit the uncertainty model for the stress concentration factor to the optimal reliability level and actual thickness of the tower. Thereafter the initial costs model was fitted to the reliability constraint to ensure that risk based optimization (RBO) gives the same optimum as RBSO. This dual optimization routine ensures that the optima found for the SHM equipped structure, using risk based optimization, is not just corresponding to the cost-benefit of a lower safety level, but is the actual value of SHM, because the structure was initially risk-optimized.

To model the fatigue crack growth, an FM model is fitted to the SN model in beta-space, following the procedure described e.g. in Straub [11]:

$$\min_{x_1 \ldots x_N} \sum_{t=1}^{T_{sl}} \left(\beta_{SN}(t) - \beta_{FM}(t; x_1 \ldots x_N)\right)^2 \tag{10}$$

The fitted parameters are ln(C) and initial crack size a_0 and the goodness of fit was visually verified by overlaying the beta curves and the probability of failure curves. A parametrical model for the geometry function Y for a circumferential through-crack from [12] is used. This also means that no closed form solution for the FM model exists, and a numerical crack simulation was used to estimate the probability of failure.

2.1 Operational evaluation and feature selection

The damage type is selected as fatigue driven horizontal, circumferential cracks as this is basis for the fatigue design of the tower.

The damage sensitive features can be chosen from any range of directly or indirectly measurable parameters. Accelerations and deflections are examples of directly measurable features, whereas mode shapes, eigenfrequencies and damping are require some amount of data condensation. The key to selecting damage sensitive features is sensitivity to damage while being insensitive to natural variability due to environmental or operational effects. Unfortunately, modal parameters display large sensitivity to these environmental effects and thus robust identification of the features is a major issue for successful modal based SHM, see [13]. Figure 2 shows the scale of the relative changes in modal parameters for the lower global modes of a wind turbine tower corresponding to a circumferential crack at all positions on the tower height.

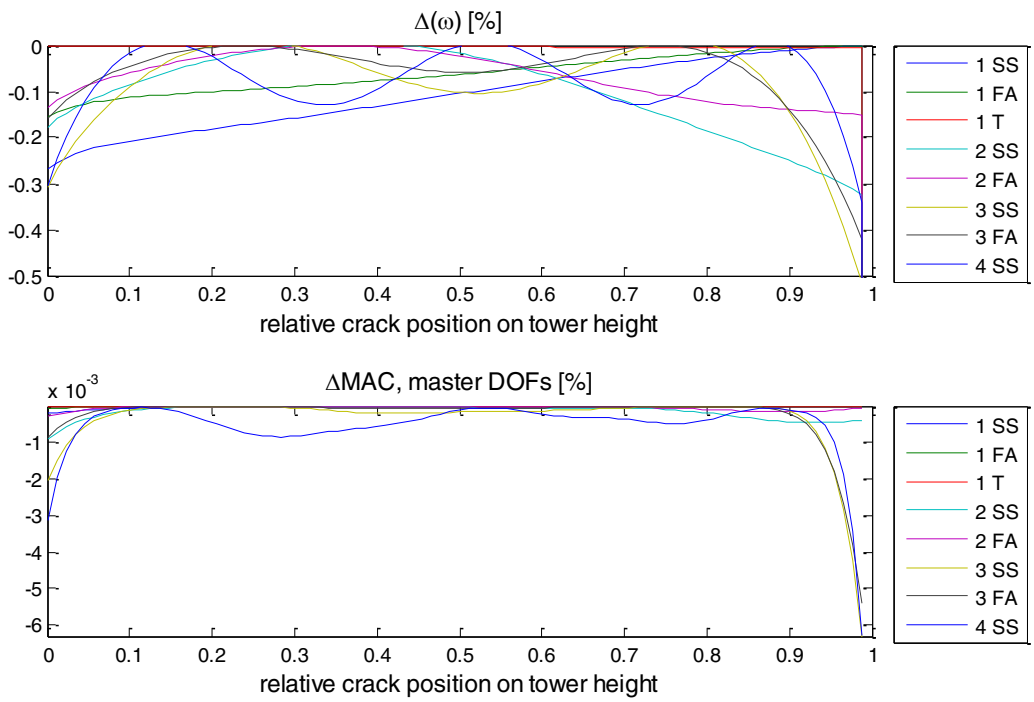

Figure 2, percent changes in modal parameters for the first 8 global modes of a wind turbine tower modelled with a high order shell model. The damage corresponds to a circumferential crack of length = 5% of circumference. The MAC values are based on model reduction to translatory master DOFs.

The modal properties still have high dimensionality, which is non-optimal for damage sensitive features. Therefore a "direct damage detection method" is used as means of reducing the dimensionality of the features to smaller vectors. Detection of damage requires a decision parameter, such as a threshold or a classification rule. For uni- or bivariate features, a threshold is the obvious type classifier, but in the multivariate case pattern recognition algorithms are suited. The method introduced by Parloo et al. [14] is here used to condense the features. The method is a mode shape sensitivity method, in which a database of modal data and input of modal frequencies

and mode shapes obtained from automated structural identification produce a damage feature vector. Only non-complex mode shapes are treated, making the method insensitive to non-linear parts of a response, and only the predefined classes are directly treated. Information of crack length, orientation and growth rate can only be inferred indirectly, and typically, the uncertainties related to modal identification, especially on mode shape derivatives, are too large to perform reliability updating based on the damage vector information alone.

2.2 Data acquisition

Global response measurements using accelerometers is used. The advantage of this is the relatively low number of sensors required. Comparing to localized monitoring, large civil structures require a very large sensor network for monitoring of multiple damage localizations as well as the need to install sensors directly where damage occurs, potentially causing sensor degradation issues.

2.3 Feature extraction

The feature extraction method itself is not the foci of the paper as any automated structural system identification (ID) technique can be used.

In the presented case, modal parameters are synthesized, as they are taken directly from a FE model and are artificially noised to account for structural identification error, as well as errors introduced by model reduction transformations. This approach adds an uncertainty as much information is lost in the model reduction, and as the "full" system information is used in derivation of the damage vector.

2.4 Supervised learning – classification

The feature statistics are estimated by sampling from the measured flexibility damage detection on a calibrated FE beam model with 30 elements. 14 global flexural and torsional tower modes are extracted and added 5 ‰ noise on eigenfrequencies and 2% on mode shapes. A direct static classification algorithm based on the components of the damage vector is used. The approach is that the detector selects the class with the highest value, but as the damage vector only represents information of damaged classes and not of the undamaged class, an arbitrary function of the components of the damage vector must represent the undamaged class. The function is in the following chosen as:

$$x = [u, k - \max(u)] \tag{11}$$

Where x is the classifier output, u is the damage vector and k is a constant that is selected so that the error-rate of the detector for a reference crack size is minimized.

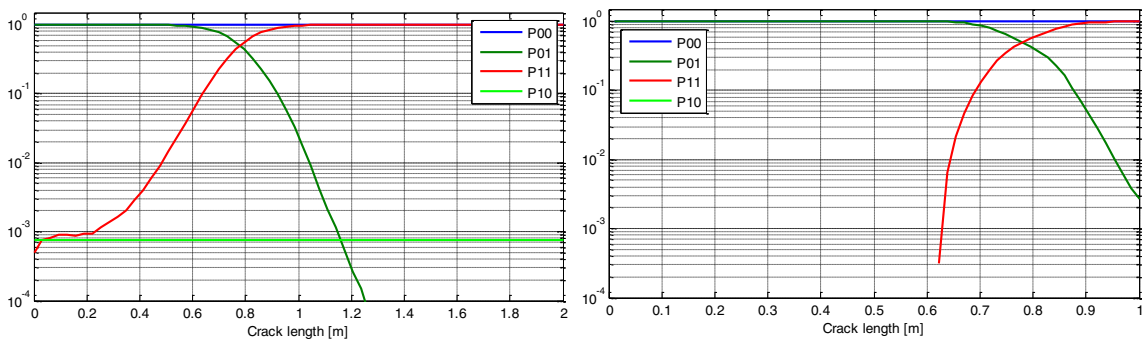

Figure 3, collected binary detector confusion probabilities as functions of targeted crack size. Left: using noised (2%) modal parameters. Right: w.o. noise on modal parameters. 8 damage locations across the tower height are assumed possible, and damage is assumed to occur at only one location at the time. P00 = true negative, P01 = false negative, P11 = true positive, P10 = false positive.

This is hardly a very effective detector, mostly because it lacks robustness to outlier data in the damage vector and because only 8 damage locations can be classified. It however serves as an adequate choice for demonstration in the current example, as an advantage over many machine learning classifiers, some direct link to the physics of the structure is preserved in the feature. Assuming that positive indication will trigger inspections of the tower, the confusion probabilities for the 8 classes may be summed to give a binary class detector statistic, which is suited for cost-benefit calculations and visualization of performance. The statistic is dependent on the actual damage geometry as the classification is based on a known damage size. The error probabilities are estimated as a function of crack length by simulation. The result is shown in Figure 3.
In the above figure, P_{11} equals the probability of indication (PoI) and P_{10} is the probability of false indication (PFI). They are linked to the probability of detection (PoD) by:

$$PoI(a) = PoD(a) + (1 - PoD(a))PFI \tag{12}$$

Where a is the crack length. The true- and false negative terms are naturally both independent of the crack size, but are included figure to illustrate the asymptotic relationship given by (12). Figure 4 is the result of sampling on the direct type classifier for the 8 damage locations. A spatial uncertainty model, derived with a parametric high order FE model of the damaged region, was used to account for variations in crack locations and geometry.

2.5 Principal results

The prior and posterior expected utility as a function of tower wall thickness t is shown in Figure 4.

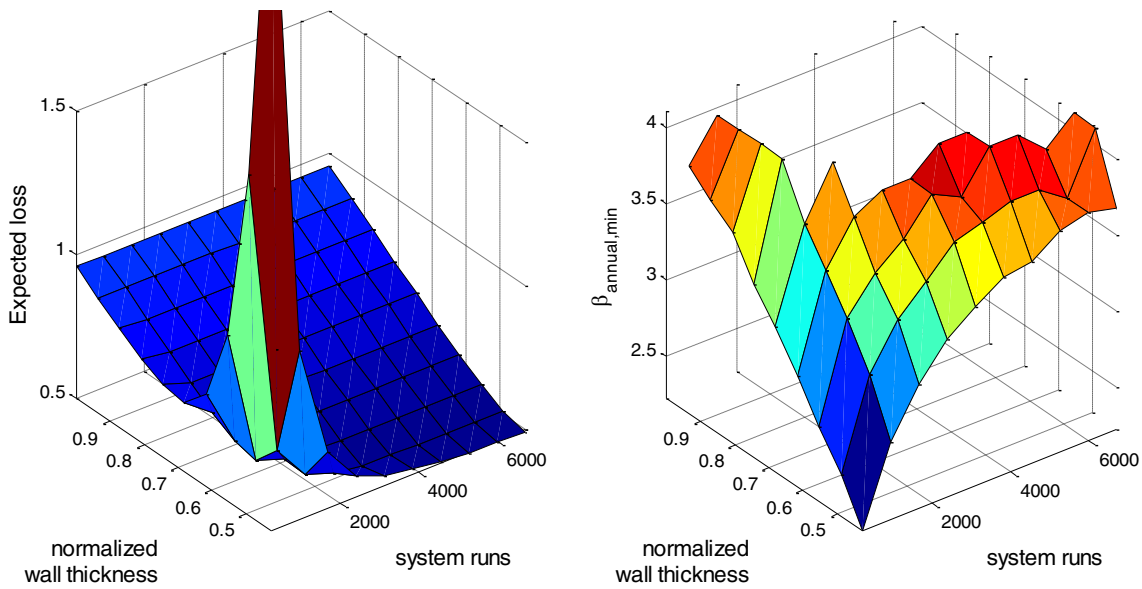

Figure 4, left: expected loss given perfect and full information of mode shapes as a function of wall thickness and SHM system runs. Right: the corresponding minimum annual reliability index. The risk optimum is observed not to violate the reliability constraint of beta = 3.3.

With the values used in this example, the wall thickness is found to be reduced by 25% and the total expected value of SHM (=$EVSI_{SHM}$) is shown to be ~40 % of the total expected loss $E[C_T]$. It must, however, be emphasized that full FE mode shapes have been used, and that the actual value will be less, taken model reduction into account. This is because the detector performance (PoD) is negatively proportional to the noise level on mode shapes while proportional to the number of channels of data acquisition. A major contribution to the overall uncertainty was observed to be the cracks impact on the modal properties of the tower. Larger change in modal properties occur when

the tower wall is unstiffened and local out-of-plane deformations are possible. These deformations at the crack tips increase ovalization, thus increasing the global rotations in the vicinity of the crack.

2.6 Conclusions and planned further work

It has been shown how the Bayesian experimental design approach to SHM can be used for vibration based SHM, where the targeted defects are very much larger than they are in ultrasound, guided waves or AE regime. The Bayesian system design approach can prove economically beneficial as total expected costs could be reduced. More work is needed in sensitivity studies with purpose of identifying and ultimately improving the predominant uncertainties in the system. As the investigation has assumed static detectors that perform classification on the current data values only, neglecting the data history, further work in the area of system design should be in the direction of dynamic policies, non-linear dynamic classifiers and on the value of filtering the data prior to classification, as all these potentially reduce the misclassification rates. Furthermore, a focus should be directed towards the costs/loss functions real world implementation. The framework and research scope is independent on the choice of the loss function, but the conclusions on economic feasibility are not, and significantly different loss functions, e.g. the cost of false alarm being much higher due to production loss, may shift cause the value of the SHM to become negative.

2.7 Acknowledgements

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