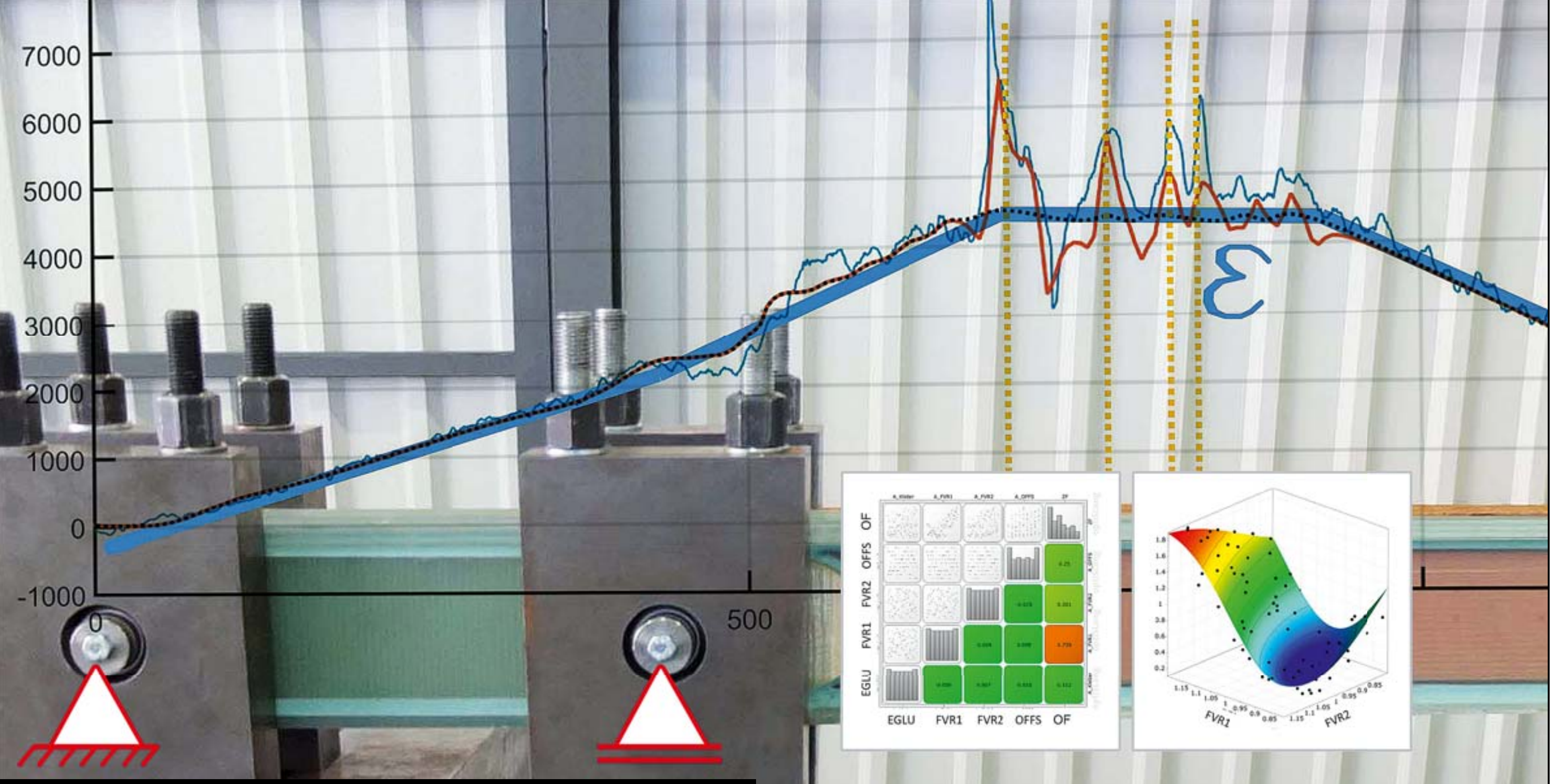

PARAMETER IDENTIFICATION BASED ON QUASI-CONTINUOUS STRAIN DATA

optiSLang was applied in a strategic approach for complementing structural health monitoring by the identification of both global as well as local parameters of a structural system using data captured by high resolution fiber optic sensing.

Introduction

What essentially distinguishes structural health monitoring (SHM) from non-destructive testing (NdT) is the application of embedded or permanently attached sensors in combination with an automated inspection process, providing high benefit in terms of maintenance cost. Beyond that, the authors want to emphasize that a comprehensive SHM methodology should contain more than pure measurement and subsequent inspection of the acquired data, even if this task is processed automatically.

Linking advanced sensing technology to parameter identification by adequate and physically meaningful models helps to bridge the gap between mere detection of structural changes and the insight into the corresponding mechanisms. However, consequences of structural degradation (e.g. cracks in concrete members) as well as imperfections (e.g. voids in laminates) are, at least in the early stage at which SHM should take effect, spatially limited and therefore hard to detect by use of measurement principles capturing rather global structural characteristics, such as modal analysis. Though, potential locations of occurrence of the above mentioned phenomena are unknown, posing the question, where to apply locally sensitive measurement devices, e.g. strain gauges or fiber-bragg gratings. The probable existence of initial defects makes the whole task even more challenging, because in this case no reference state is available to qualify changes in structural load bearing behavior.

The objective of the present work is to complement up-to-date SHM technology by identification of both global as well as local parameters of a structural system in a strategic approach based on quasi-continuous strain data. The strain signals are gained with high-definition sensing technology using the effect of Rayleigh backscattering of light waves propagating through optical fibers. These enable to capture strain signals along the fiber's path over a length of up to 50 m with a spatial resolution down to around 1 mm. A parametric structural model is calibrated by processing the measurement data in a parameter identification procedure, in which the parameters are grouped into global and local sets. Global parameters hereby pertain to properties affecting the overall structural behavior, whereas local parameters characterize spatially limited discontinuities. The identification problem is solved using a two-step approach, in which firstly parameters of a global

reference state are determined. In a second step, the parameters of local discontinuities are identified in an iterative procedure. The approach is demonstrated on a test structure representing the load carrying component of rotor blades of wind energy plants and consisting of several GFRP-laminate parts. During assembly, these are bonded to each other by glue layers, which in industrial practice turned out to be prone to imperfections, particularly air inclusions.

Parameter Identification

The large field of system identification can be divided into the domains of model-free black box systems and model-based gray box systems. While black box systems are represented by a set of mathematical expressions, gray box systems consist of a model containing a set of physically meaningful parameters. Their determination in a model-based system is called parameter identification or parameter update. In the field of SHM applications, this procedure enables the investigation of causes of changes in structural characteristics such as damage, initial faults or any loss of strength, rather than to merely detect their presence. Basically, the identification process is an iterative minimization of a vector of residuals **ε**, which contains the deviations between measured output variables $\mathbf{u_m}$ of a structure S and corresponding computed outputs $\mathbf{u_r}$ (Equation 1) of a model **SM(P)** due to an input **f**, where **f** in case of mechanical systems represents the structural load and **P** the parameter vector of the system (Fig. 1). The set **P** of parameters P_i is determined by minimizing the objective function J with respect to the vector of deviations **ε** according to Equation 2:

$$\boldsymbol{\epsilon}(\boldsymbol{P}) = \boldsymbol{u}_m - \boldsymbol{u}_r(\boldsymbol{P}) \qquad (1)$$

$$J(\boldsymbol{P}) = \boldsymbol{\epsilon}^T \boldsymbol{\epsilon} \rightarrow MIN \qquad (2)$$

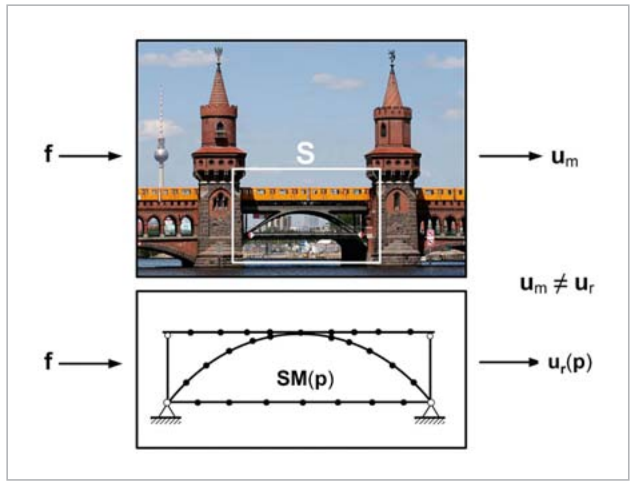

Fig. 1: Structure S and structural model SM under load f with responses u_m and u_r

The objective function is in many cases defined by the well-known least squares regression method and its minimization represents an optimization task, which can be performed by use of a variety of different optimization methodologies. Modal properties as natural frequencies and mode shapes are comparatively easy to gain and offer information of high density about a structures global behavior. Therefore, in the majority of applications, dynamic properties of systems are used for parameter identification. Static answers are usually more elaborate concerning instrumentation and application of test loads. Local discontinuities, such as cracks or initial defects, have only little or even hardly measurable effect on the global outputs of structural systems, independently from being of dynamic or static nature.

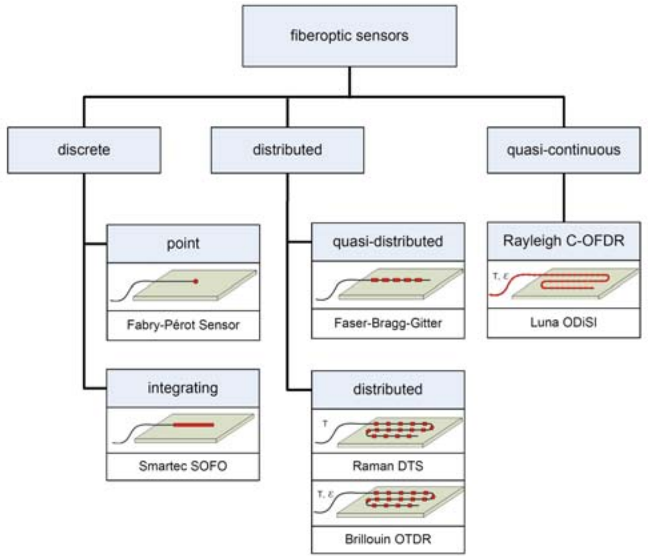

Fig. 2: Outline on sensor topologies

By understanding every structure's properties to be rather of global or local nature, it seems promising to separate parameter identification into steps, which firstly focus on global characteristics and are aimed in a second step to identify local properties such as damage.

Rayleigh-based fibre optic sensing

Fiber optic sensors have intrinsic properties which make them ideally suited for applications in the field of SHM. Single, multiple or a great many of sensors can be realized in a single fiber of diameter around 200 microns or even less. They resist rough environmental conditions such as strong magnetic fields, chemical aggressive media as well as high temperature or radioactive radiation. Beyond that, their small scale qualifies them for installation inside and on surface of components respectively. Besides, the possibility of realizing many sensors in a single fiber helps reducing cost.

Fibre optic sensing topologies

Fiber optic sensing systems may be categorized on the basis of their topology as diagramed in Fig. 2. In the present work, strain sensing based on Rayleigh backscattering evaluated by coherent optical frequency domain reflectometry (c-OFDR) was used. This technology allows for the definition of a very large number of sensors in the fiber, leading to extremely high spatial resolution of the captured strain signal. In the sense of digital (discrete) data processing, the signal can be regarded as continuous, although this is not correct in a strict mathematical sense. Therefore the designation quasi-continuous is proposed by the authors.

Rayleigh OFDR strain measurement

Sensors in a c-OFDR system can be realized in commercially available telecom fibers without any special adaption such as writing bragg gratings. The measurement principle is based on the analysis of the backscattered portion of light sent into a fiber, which occurs due to inevitable disturbances. These appear in every material and so they do as well in optical fibers. Quantity, length and position of sensors are determined in the measurement unit, dividing the length of the sensing fiber into a number of equally spaced segments (Fig. 3, top), each of which being one sensor. A light pulse sent into the fiber by a tuneable laser source is superimposed with a reference signal in a Mach-Zehnder interferometer and the interference of measurement and reference signal is evaluated in the measurement unit for each of the segments. It is beyond the scope of this contribution to go into further detail and a more elaborate description of the principle by Samiec is publicly available. Accuracy and Sensitivity as well as noise level are comparable to strain gauges or fiber bragg gratings, although the dynamically usable frequency range is (to date) rather limited.

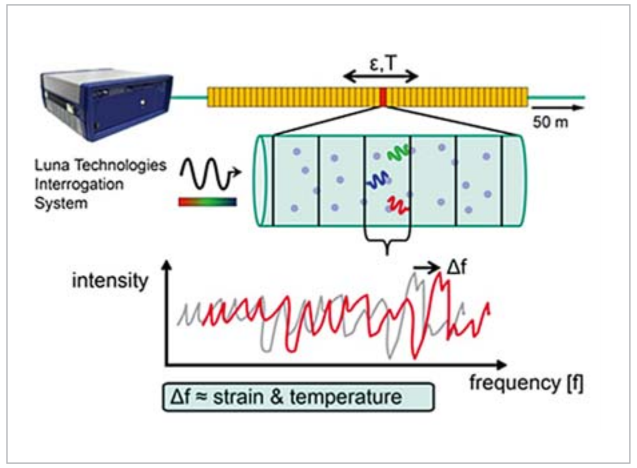

Fig. 3: Analysis of Rayleigh scattering (source: Luna Innovations Inc.)

Application

Although having arrived quite recently on the market, the technology is already applied in many industrial and scientific applications. Fibers can be integrated into structural components as well as mounted on its surface, e.g. by bonding.

Parameter identification on quasi-continuous strain data

In the present work, a method for parameter identification is proposed, which, due to a two step approach, is able to determine global parameters belonging to a reference state as well as local parameters of discontinuities, e.g. initial defects. Obviously, in the case of initial defects no intact state is measurable but fortunately, quasi-continuous strain data offers enough information to recover a state without influence of local defects which can be regarded as a reference.

Stepwise Approach

The shape function can be formulated by a finite element model, in which, at certain locations inside the structure, a number of i discontinuities in the form of e.g. air inclusions is present, see Fig. 4. A discontinuity is characterized by the parameters of location fx, depth under surface fy and length dx, but basically any other cluster of parameters describing any type of discontinuity is possible. The parameters are grouped to sets $\mathbf{P}i$ as stated in Equation 3.

$$P_i = \begin{pmatrix} fx_i \\ fy_i \\ dx_i \end{pmatrix} \qquad (3)$$

The scalar shape function, i.e. the strain signal, can be written according to Equation 4, taking into account that the relationship inside the function is represented by the finite element model. The model should allow for covering a number of i discontinuities, so that the final shape function N is a linear combination of $N1, N2 \ldots Nn$.

$$N_i \;=\; N_i(\mathbf{P_i}) = \; N_i(\,fx_i, fy_i, dx_i) \qquad (4)$$

Loading the structure consequently yields to the formation of a peak in the strain signal whose shape is linked with the parameters of location and extent of the discontinuity. Therefore the local signal shape is defined indirectly, based on parameters of the finite element model. This, in turn, implies that the character of the discontinuity has to be known to a certain degree, which also provides for physical meaningful results.

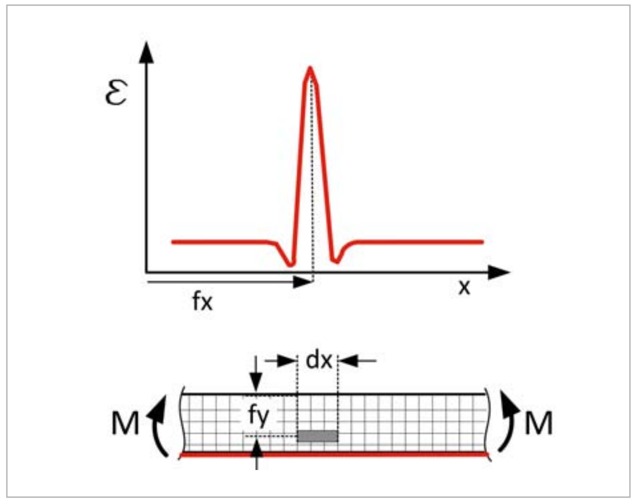

Fig. 4: Shape function used in the stepwise approach; upper figure: shape function, lower figure: structure; sensor path highlighted in red; load represented by bending moment

Procedure

The identification process is divided into a global step and a local step, in the following called step A and step B respectively, see Fig. 5. The result of step A, i.e. set A, containing the identified global parameters, is passed to step B and is fixed in the subsequent identification of the local parameters. The method should not be limited with respect to the number of discontinuities and therefore step B runs iteratively with substeps B1,B2,...Bn until reaching an exit condition. At the end of step B, global and local parameters are identified. In both steps the sum of least squares of all support points (i.e. strain values of all sensors) is used as objective function.

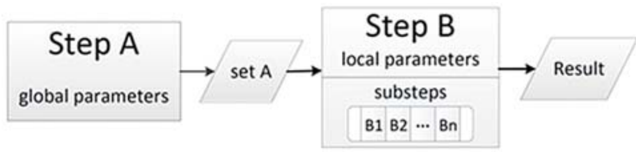

Fig. 5: Simplified scheme of the stepwise approach

Roughly speaking, the computational effort of solving an optimization problem depends exponentially on the number of parameters. Grouping parameters into physically consistent sets in the way shown above is therefore not only advantageous in terms of meaningfulness of the solution but also with respect to efficiency. In the method presented here, the parameter space is divided into independent subspaces allowing for the solution of several small optimization problems instead of one large task.

Simulation example

The process should be demonstrated in this section by use of a simulation example. It consists of a simply supported beam which is loaded at two points by equal forces, as shown in Fig. 6. Global parameters of the system are the distance *len*1 between one of the load points and the adjacent support, the Young's modulus *E* and the Poisson's ratio ν of the material. Local parameters are the location index nx_i in longitudinal direction, the location fy_i in the cross-section in direction of the load and fz_i in the cross-section in direction perpendicular to the load direction. This test setup generates in the (virtual) sensor a strain state as depicted as reference in Fig. 7.

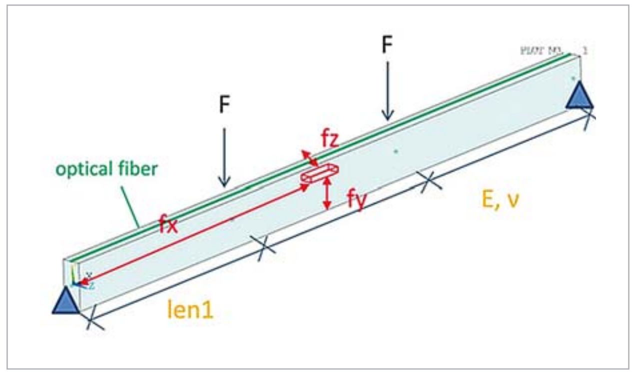

Fig. 6: Simulation example simple beam in 4-point bending test; yellow -global parameters, red -local parameters

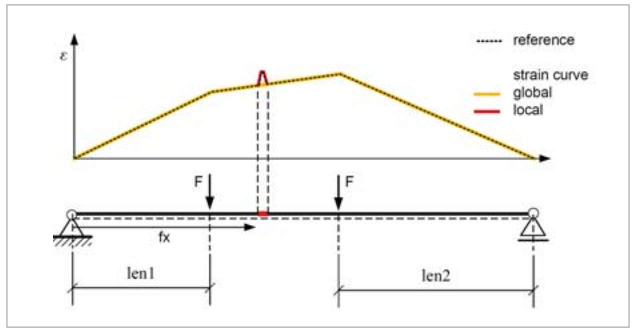

Fig. 7: Strain curves due to global and local parameters

It can be divided due to its causes into a signal of global and local strain respectively. Evaluating the objective function in a sensitivity analysis and subsequently generating a response surface, the fundamental difference in character of global and local signals is clearly visible. The response surface for step A is showing a smooth, monotonic and convex shape with a well defined minimum as can be seen in Fig. 8a while it shows a single, sharply bounded minimum in within an area of low gradient (Fig. 8b).

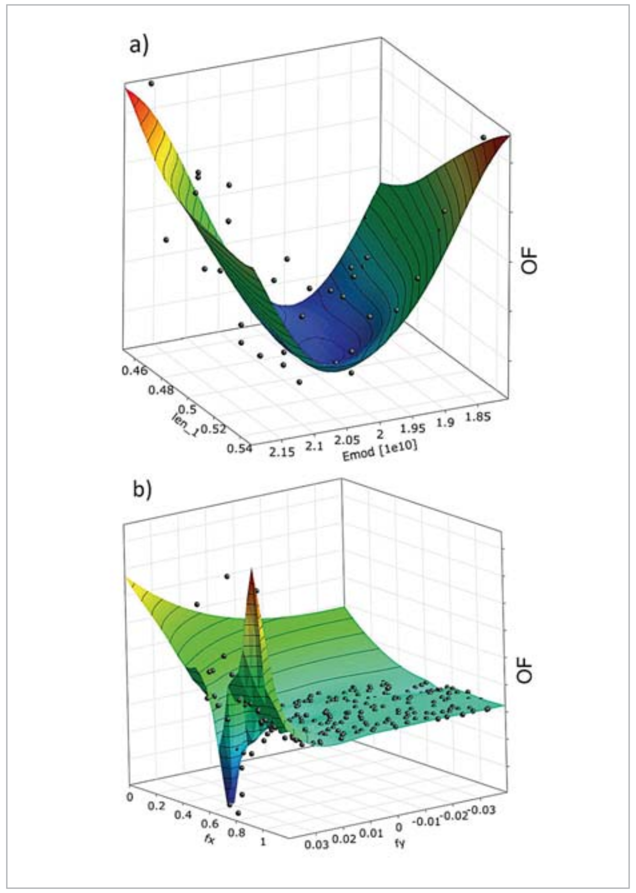

Fig. 8: Response surfaces for step A parameters and step B parameters

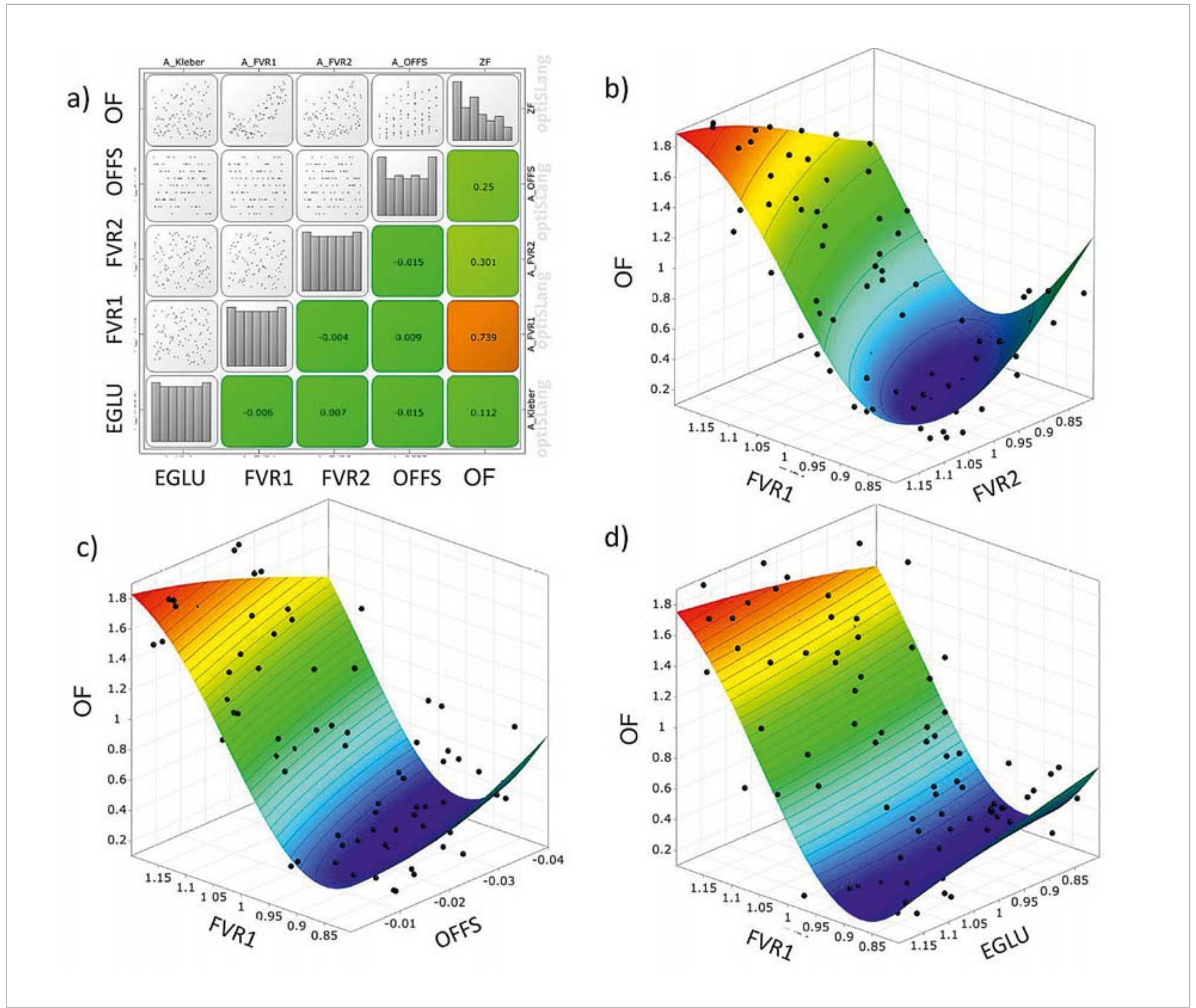

Fig. 9: Extended correlation matrix (a) and meta models (b -c) for 1-step approach

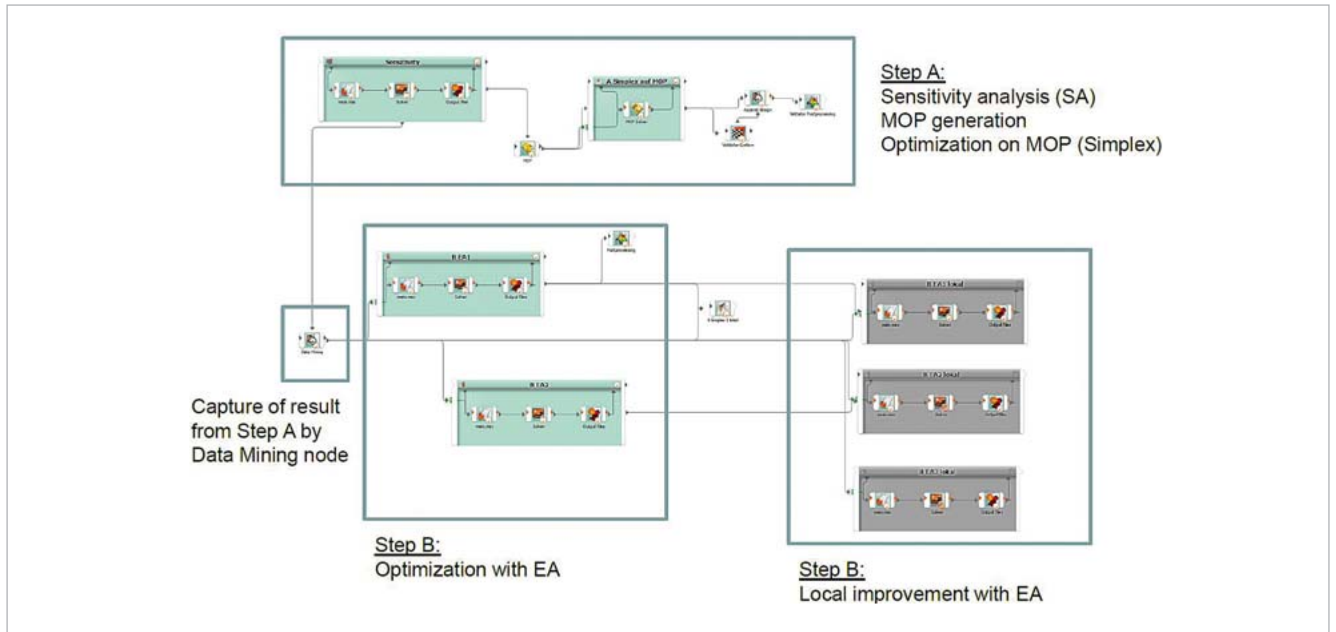

Fig. 10: Implementation of the 2-step approach in optiSlang

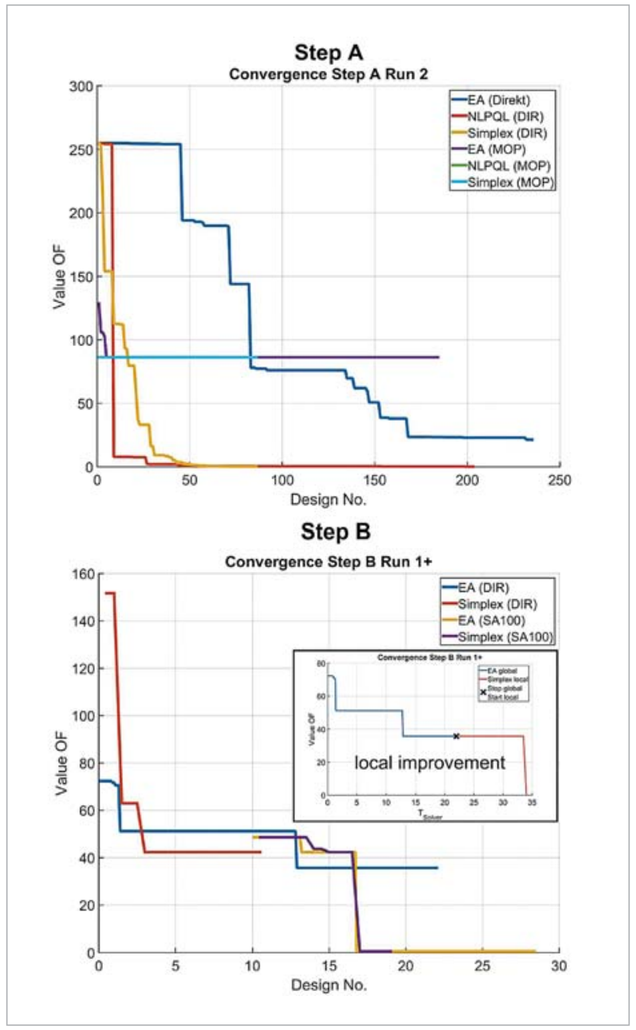

Fig. 11: Performance comparison of optimization algorithms in step A and step B

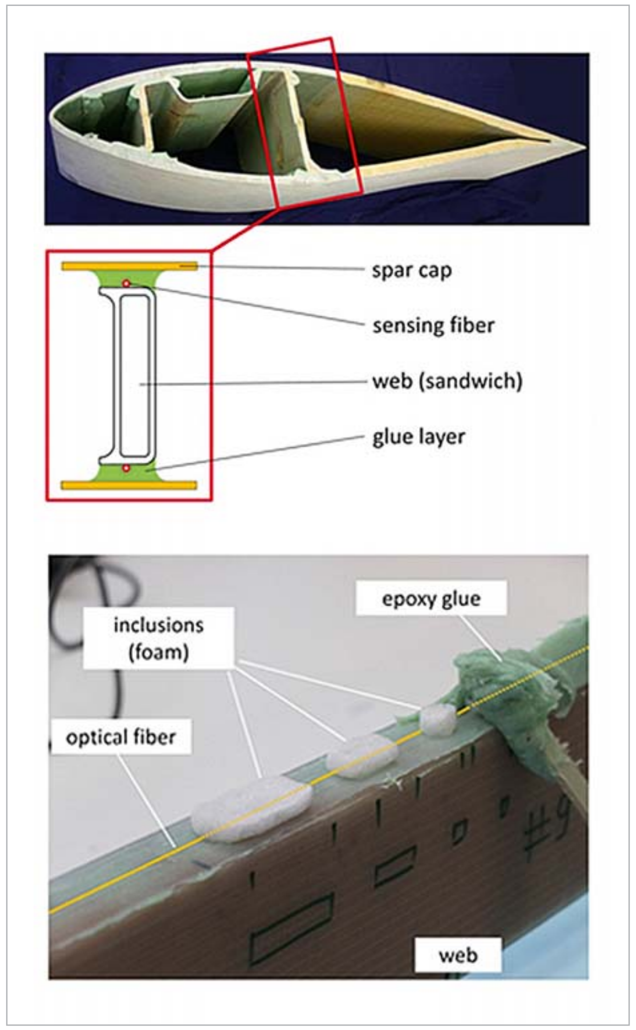

Fig. 12: Test specimen; Subcomponent of rotor blade of wind energy plants and its assembly; air inclusions are simulated using foam bodies

This determines the kind of optimization algorithm to be used for the minimization of the objective function. For step A, basically any algorithm is able to deliver a sufficient solution, although gradient based or simplex optimizers show better performance. For step B, random sampling based optimizers such as evolutionary algorithms are preferable. In this work, performance aspects were elaborately investigated. However, their discussion goes beyond the scope of this article.

All parameters, global as well as local, were identified properly by the application of the method proposed here whereas a one-step approach can only deliver the global parameters. This can be explained by the low impact of the local peaks in the strain signal on the objective function. The extended correlation matrix Fig. 9a shows this relation: Only the global parameters LEN1 and EMOD have significant influence on the objective function (ZF) whereas correlation coefficients of local parameters (nx, fy) are almost zero.

The setup in optiSlang shows Fig. 10. Step A starts with a sensitivity analysis to assess input parameters with respect to their importance followed by the generation of the metamodel (MOP). The optimization is subsequently carried out on the MOP and its result is validated. Due to the rather smooth and convex character of the response surface, use of a simplex optimization algorithm delivers both accurate results and good performance. A data mining node helps to capture the optimization result and to hand it over to step B of the procedure in which local parameters are identified by an optimization with an algorithm of rather global nature such as an evolutionary algorithm (EA). The quality of the result of this step can be improved with a following iterative process. Aspects of the selection of appropriate optimization algorithms were already discussed above and can be affirmed by comparison of the performance of different algorithm types in this simulation example Fig. 11.

Experimental application

The stepwise method described above was applied to the test of a subcomponent of rotor blades of wind energy plants shown in Fig. 12. Development and use of this component is described in detail by Sayer et al.. It consists of GFRP-laminated spar caps and a sandwich web structure bonded to

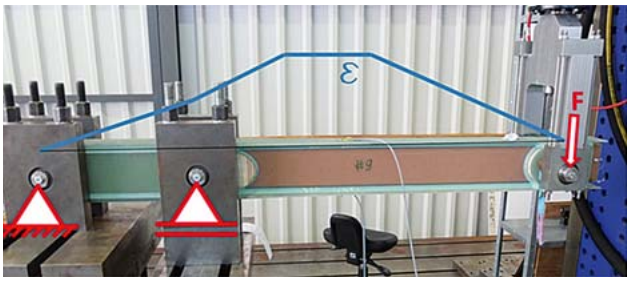

Fig. 13: Test setup for rotor blade component; shape of strain signal in blue

each other by epoxy-based glue. The objective of the investigation shown here was to detect representative voids inside the glue layer which appear during manufacture. For this purpose, optical fibers were integrated into the bondline by mounting the fiber to the surface of the web as shown in Fig. 12. The component is supported and loaded as can be seen in Fig. 13 (see next page). Due to variation of the number of layers of the spar caps, a partly constant strain signal is generated which allows for the investigation of the effect of disturbances in the bondline. Global parameters to be identified were the stiffness of the unidirectional and biaxial layers of the composite components, the Young's modulus of the glue material and a variation in thickness of the spar caps. The location of inclusions in longitudinal direction as well as their location in the cross-section of the glue layer on the tension side were defined as local parameters.
In a total of 10 iterations in step B, all larger artificial voids could be identified in location and extent. As can be seen, some deviations of the simulated signal to the measured strain signal remain. Reason is, that not all details of the rather complex inner structure could be integrated into the finite element model. However, also the identified global stiffness parameters are showing reasonable values. As effect of a number of smaller (unintended) discontinuities also visible in CT-scans (but not documented here) a lot of smaller peaks in the strain signal can be recognized.

Conclusions

A stepwise static parameter identification method based on high-resolution quasi-continuous fiber optic strain sensing is used to identify global and local structural parameters. The approach allows for the determination of an intact reference state and local discontinuities as well. Being based on a proper structural model, these can not only be detected but also quantified. Grouping parameters belonging together in a physical sense into sets supports efficient optimization of the objective function and leads to physically meaningful results. The proposed method is applied to a specimen representing the loadbearing component of rotor blades of wind energy plants in a bending test. Initial defects in form of air inclusions in the bond line are identified with respect to location and extent. In near future, the method should be extended to dynamic applications, too.

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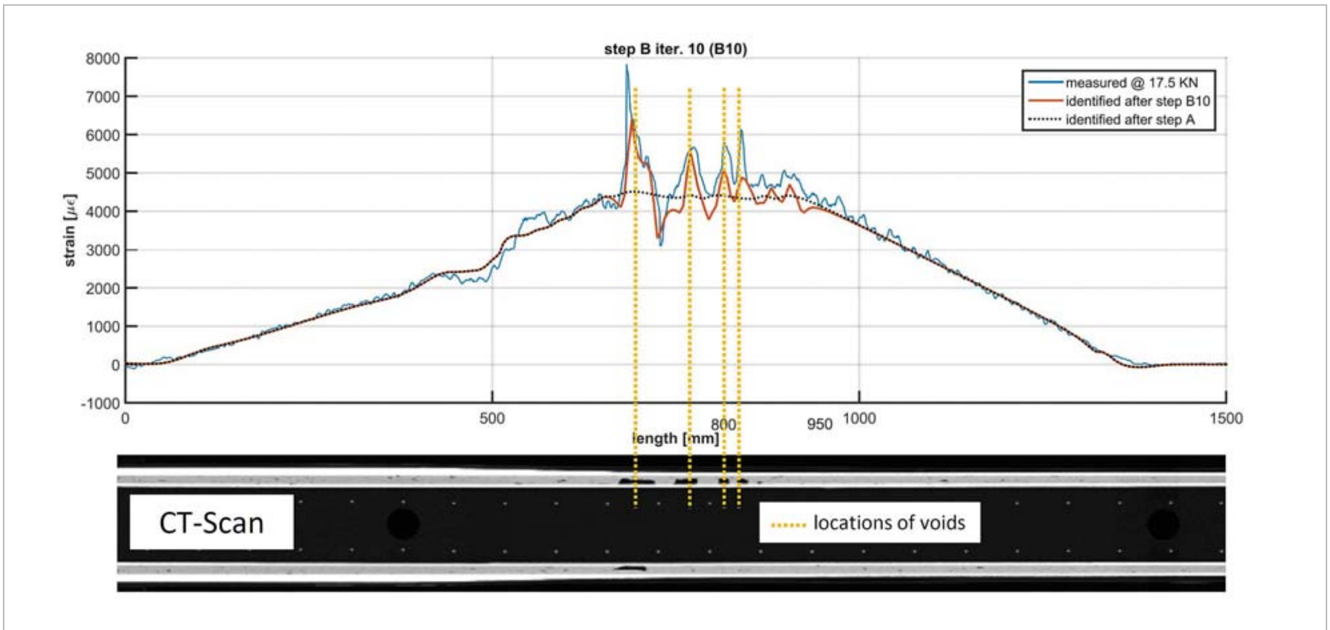

Fig. 14: Results of identification; comparison to CT-scan data