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# OUTPUT-ONLY ANALYSIS FOR EXPERIMENTAL DAMAGE DETECTION OF A TIED-ARCH BRIDGE

**C. Ebert***, **A. Lenzen***

**HTWK Leipzig - Fachbereich Bauwesen*
*Karl-Liebknecht-Straße 132, 04277 Leipzig*
E-mail: cebert@fbb.htwk-leipzig.de, lenzen@fbb.htwk-leipzig.de

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**Abstract.** *In civil engineering it is very difficult and often expensive to excite constructions such as bridges and buildings with an impulse hammer or shaker. This problem can be avoided with the output-only method as special feature of stochastic system identification. The permanently existing ambient noise (e.g. wind, traffic, waves) is sufficient to excite the structures in their operational conditions. The output-only method is able to estimate the observable part of a state-space-model which contains the dynamic characteristics of the measured mechanical system. Because of the assumption that the ambient excitation is white there is no requirement to measure the input. Another advantage of the output-only method is the possibility to get high detailed models by a special method, called polyreference setup. To pretend the availability of a much larger set of sensors the data from varying sensor locations will be collected. Several successive data sets are recorded with sensors at different locations (moving sensors) and fixed locations (reference sensors). The covariance functions of the reference sensors are bases to normalize the moving sensors. The result of the following subspace-based system identification is a high detailed black-box-model that contains the weighting function including the well-known dynamic parameters eigenfrequencies and mode shapes of the mechanical system.*

*Emphasis of this lecture is the presentation of an extensive damage detection experiment. A 53-year old prestressed concrete tied-arch-bridge in Hünxe (Germany) was deconstructed in 2005. Preliminary numerous vibration measurements were accomplished. The first experiment for system modification was an additional support near the bridge bearing of one main girder. During a further experiment one hanger from one tied arch was cut through as an induced damage. Some first outcomes of the described experiments will be presented.*

## 1 INTRODUCTION

Technical systems are damaged by overloading, fatigue, aging and environmental influences. When structures of civil engineering are planned for a finite life time, monitoring with respect to damage is one chance to guarantee safe functionality.

The life time of a structure can be split into three main phases, which are the design phase, the construction phase and the utilization phase. With regard to their functionality these three phases differ as follows:

- The design of a structure deals with the specification of the type of structural system, of loads and other influences. Such specification depends, of course, on the demands made on the structure, especially under safety and economical aspects.
- The construction phase covers the quality examination of the building materials, the safety of the planned construction and the safety and examination of the various stages of a structural building, in order to realize the goals defined during the design phase.
- The utilization phase starts with the release of the structure and then the structure is exposed to manifold influences, e.g. aging and fatigue processes, as well as further planned and non-planned external events.

An appropriate instrument to guarantee structural safety and economic efficiency is the monitoring of a structure with comparatively little costs for maintenance and monitoring in contrast to the high costs for structural repair or maintenance work, which would be avoided.

In this paper it is proposed to identify the dynamic characteristic of a structure by vibration measurements. In the case of damage this characteristic will be altered. Here a black - box model of the system, which has to be identified first, will be used to detect and localize system variations instead of the so called model based damage analysis where finite elements are used to establish a numerical model of the system. The black box model for the intact system is compared with the black box model of the damaged monitored system.

## 2 MECHANICAL SYSTEMS - IDENTIFICATION

There are two main concepts for the modelling of mechanical systems. Here it will be called:

I. analytical physical - or white - box - modelling,

II. black - box - modelling.

A combination of these methods may be named

III. hybrid - or grey - box - modelling.

Simple systems can be analyzed by collecting all physical, chemical and other information and setting up all corresponding equations to get a mathematical model on an analytical physical basis. If it is not practicable to set up physical equations of a system black - box modelling can be used to describe the input - output relation of the system.

### 2.1 Black - Box Model

Basic theoretical concepts and methods for the black - box generation can follow on the basis of the system theory. According to the system theory and to the principle cause - effect, technical systems are generally formulated as transfer systems, whereas the cause is assigned to the input and the effect to the output of a system.
The mathematical description can be done in the time domain or in the frequency domain, where the time domain is advantageous especially for non-linear system behaviour.
The linear system theory is most widely developed. For linear models the superposition principle is valid. Three different mathematical formulations are in use for continuous linear systems:

a. The differential equation is formulated as state equation

$$\begin{aligned} \dot{\mathbf{x}}(t) &= \mathbf{A}\,\mathbf{x}(t) + \mathbf{B}\,\mathbf{u}(t) \\ \mathbf{y}(t) &= \mathbf{C}\,\mathbf{x}(t) + \mathbf{D}\,\mathbf{u}(t). \end{aligned} \tag{1}$$

b. The weighting function (or the matrix of weighting functions). $\lambda_l$ are the eigenvalues of the matrix $\mathbf{A}$

$$\begin{aligned} \mathbf{h}(t) &= \mathrm{e}^{\mathbf{A}t} \\ h_{ij}(t) &= \sum_l k_{ij\,l} e^{\lambda_l t}. \end{aligned} \tag{2}$$

c. The frequency response function (or the matrix of frequency response functions)

$$\begin{aligned} \mathbf{H}(j\Omega) &= \mathbf{C}(j\Omega\mathbf{I} - \mathbf{A})^{-1}\mathbf{B} + \mathbf{D} \\ h_{ij}(j\Omega) &= \sum_l \frac{(A_{ij})_l}{j\Omega - \lambda_l} = \frac{\sum_l (b_{ij})_l (j\Omega)^l}{\sum_k (a_{ij})_k (j\Omega)^k} \end{aligned} \tag{3}$$

Frequency response and weighting functions are connected by the Fourier or Laplace transformation. In the following section it is described how black-box models can be identified of stochastic excited mechanical structures.

### 2.2 Stochastic Systemidentification

The fundamental acceptance during system identification by stochastic excited structures is that the ambient noise is white. White noise is characterized by an identical power spectrum over all frequencies. For this special case the correlation function is defined as dirac-impulse. Because of this the algorithm to identify the state-space parameter is comparable to identification with deterministic excitation. Hence the averaged correlation functions of the measured signals are used for realization and not the measured signals themselves.
For system identification with stochastic excitation the state space model is extended by an white noise process $\mathbf{w}$ at the input and a noise process $\mathbf{v}$ for measurement errors at output.

$$\begin{aligned} \mathbf{x}_{k+1} &= \mathbf{A}\mathbf{x}_k + \mathbf{B}\mathbf{u}_k + \mathbf{w}_k \\ \mathbf{y}_k &= \mathbf{C}\mathbf{x}_k + \mathbf{D}\mathbf{u}_k + \mathbf{v}_k \end{aligned} \tag{4}$$

For deterministic input equal zero it is possible to show that the averaged correlation function $\mathbf{R_{yy}}$ of measured output can be parameterized:

$$\begin{aligned} \mathbf{R}_{\mathbf{yy},(\tau_k>0)} &= \mathbf{CA}^k E[\mathbf{x}_k\mathbf{x}_k^T]\mathbf{C}^T + \mathbf{CA}^{k-1}E[\mathbf{w}_k\mathbf{v}_k^T] \\ &= \mathbf{CA}^k\mathbf{P}_{xx}\mathbf{C}^T + \mathbf{CA}^{k-1}\mathbf{R}_{12} \\ &= \mathbf{CA}^{k-1}(\mathbf{AP}_{xx}\mathbf{C}^T + \mathbf{R}_{12}) \\ &= \mathbf{CA}^{k-1}\mathbf{M} \end{aligned} \tag{5}$$

The discrete values of the averaged correlation function $\mathbf{R_{yy}}$ will be used to arrange a Hankel matrix.

$$\mathbf{H} = \begin{bmatrix} \mathbf{CA}^0\mathbf{M} & \mathbf{CA}^1\mathbf{M} & \mathbf{CA}^2\mathbf{M} & \cdots \\ \mathbf{CA}^1\mathbf{M} & \mathbf{CA}^2\mathbf{M} & \mathbf{CA}^3\mathbf{M} & \cdots \\ \mathbf{CA}^2\mathbf{M} & \mathbf{CA}^3\mathbf{M} & \mathbf{CA}^4\mathbf{M} & \cdots \\ \vdots & \vdots & \vdots & \ddots \end{bmatrix} \hat{=} \begin{bmatrix} \mathbf{R}_{yy,1} & \mathbf{R}_{yy,2} & \mathbf{R}_{yy,3} & \cdots \\ \mathbf{R}_{yy,2} & \mathbf{R}_{yy,3} & \mathbf{R}_{yy,4} & \cdots \\ \mathbf{R}_{yy,3} & \mathbf{R}_{yy,4} & \mathbf{R}_{yy,5} & \cdots \\ \vdots & \vdots & \vdots & \ddots \end{bmatrix} \tag{6}$$

The theoretical dimension of these Hankel matrix is infinite but the rank is finite. To extract the parameters of the associated state space model the singular value decomposition will be used. The Hankel matrix will be split into the observability matrix $\mathbf{\Gamma}$ and the controllability matrix $\mathbf{Q}$.

$$\begin{aligned} \mathbf{H} &= \mathbf{U}_1\mathbf{\Sigma}_1\mathbf{V}_1^T \\ &= \mathbf{\Gamma}_1\mathbf{Q} \\ &= \begin{bmatrix} \mathbf{CA}^0 \\ \mathbf{CA}^1 \\ \mathbf{CA}^2 \\ \vdots \end{bmatrix} \begin{bmatrix} \mathbf{A}^0\mathbf{M} & \mathbf{A}^1\mathbf{M} & \mathbf{A}^2\mathbf{M} & \cdots \end{bmatrix} \end{aligned} \tag{7}$$

The searched parameters are contained in the matrix blocks:

$$\begin{aligned} \mathbf{A} &= \mathbf{\Gamma}_1^\dagger\mathbf{\Gamma}_2 \\ \mathbf{C} &= \mathbf{\Gamma}_1(1:q, 1:n) \\ \mathbf{M} &= {}^n\mathbf{Q}(1:n, 1:p) \end{aligned} \tag{8}$$

Further details for this parameter identification are in the literature [4].
The identified models contain the dynamic characteristics of the underlying mechanical structure. A transformation in the modal room shows the modes and poles of the structure. But the identified models do not describe the measured system completely. Unknown is the gain of the transfer function, because only the output of the system will be measured. The input will not be measured but accepted as white noise. Therefore this procedure is called output-only.
It is possible to use the Kalmann filter to find a complete model that contain the gain and the dynamic behavior of the system. The Kalmann filter estimate the future state $\hat{\mathbf{x}}_{k+1}$ recursive by minimization of an error between $\mathbf{y}_k$ and $\hat{\mathbf{y}}_k$. The Kalmann gain $\mathbf{K}$ leads back the error $\mathbf{e}_{k-1} = \mathbf{y}_{k-1} - \hat{\mathbf{y}}_{k-1}$ in the model. The error is the new information in future time and it is called innovations. It can be shown that these innovations show a white process. Thus you receives the following innovation model:

$$\begin{aligned} \hat{\mathbf{x}}_{k+1} &= \mathbf{A}\hat{\mathbf{x}}_k + \mathbf{K}\mathbf{e}_k \\ \mathbf{y}_k &= \mathbf{C}\hat{\mathbf{x}}_k + \mathbf{I}\mathbf{e}_k \end{aligned} \tag{9}$$

This state space model contains the parameters $\mathbf{A}$ and $\mathbf{C}$ computed by the output-only method and the Kalmann gain $\mathbf{K} \equiv \mathbf{B}$. This model can be interpreted as the searched complete state space model that describes the dynamic and the gain of the underlying mechanical structure. To find the Kalmann gain it is necessary to solve the Riccati equation.

$$\begin{aligned}\hat{\mathbf{P}}_{xx} &= \bar{\mathbf{A}}\hat{\mathbf{P}}_{xx}\bar{\mathbf{A}}^T + (\mathbf{M} - \bar{\mathbf{A}}\hat{\mathbf{P}}_{\mathbf{xx}}\bar{\mathbf{C}}^{\mathbf{T}})(\mathbf{R}_{\mathbf{yy},(\mathbf{0})} - \bar{\mathbf{C}}\hat{\mathbf{P}}_{\mathbf{xx}}\bar{\mathbf{C}}^{\mathbf{T}})^{-\mathbf{1}}(\mathbf{M} - \bar{\mathbf{A}}\hat{\mathbf{P}}_{\mathbf{xx}}\bar{\mathbf{C}}^{\mathbf{T}})^{\mathbf{T}} \\ &= \bar{\mathbf{A}}\hat{\mathbf{P}}_{xx}\bar{\mathbf{A}}^T + (\mathbf{M} - \bar{\mathbf{A}}\hat{\mathbf{P}}_{\mathbf{xx}}\bar{\mathbf{C}}^{\mathbf{T}})(\mathbf{E}(\mathbf{e_k}\mathbf{e_k^T}))^{-\mathbf{1}}(\mathbf{M} - \bar{\mathbf{A}}\hat{\mathbf{P}}_{\mathbf{xx}}\bar{\mathbf{C}}^{\mathbf{T}})^{\mathbf{T}} \end{aligned} \tag{10}$$

The parameters $\hat{\mathbf{A}}, \hat{\mathbf{C}}$ and $\mathbf{M}$ are known by the first estimation step. $\hat{\mathbf{P}}_{xx}, \mathbf{R}_{yy,(0)}$ and $\mathbf{E}(\mathbf{e_k}\mathbf{e_k^T})$ are the covariances of the state, the measured output and the innovations. If a solution of the Riccati equation exists, you can obtain the Kalman gain of the model.

$$\mathbf{K} = (\mathbf{M} - \bar{\mathbf{A}}\hat{\mathbf{P}}_{\mathbf{xx}}\mathbf{C}^{\mathbf{T}})(\mathbf{E}(\mathbf{e_k}\mathbf{e_k^T}))^{-\mathbf{1}} \tag{11}$$

Overall the solution of the Riccati equation is only possible, if the correlation function is positiv definite. There are a few proposals in literature to guarantee a solution. But by the experiences of the authors it remains an open problem in large scale stochastic realization theory. The research is ongoing.

### 2.2.1 Polyreference Method

For experimental tests a measuring system with limited number of sensors is usually available. For high detailed models the available system is not sufficient on large structures possibly. A damage localization on low detailed models is difficult especially if no sensor is available at the damage location. The polyreference method is an add-on of the output-only method. This method allows to identify high detailed models in spite of a limited number of sensors. Instead of an individual measurement several records $J$ are accomplished. Each individual record contains data from a group of reference sensors $\mathbf{y}_t^{ref,j}$, whose position is fixed at all records, and data from a group of moving sensors $\mathbf{y}_t^j$, whose position is changed with each record. The measured values of each individual record can be stored in time-dependent vectors as follows:

$$\underbrace{\begin{pmatrix}\mathbf{y}_t^{(ref,1)} \\ \mathbf{y}_t^{(1)}\end{pmatrix}}_{record\ 1} \quad \underbrace{\begin{pmatrix}\mathbf{y}_t^{(ref,2)} \\ \mathbf{y}_t^{(2)}\end{pmatrix}}_{record\ 2} \quad \cdots \quad \underbrace{\begin{pmatrix}\mathbf{y}_t^{(ref,J)} \\ \mathbf{y}_t^{(J)}\end{pmatrix}}_{record\ J} \tag{12}$$

Each record $j$ $(1 \leq j \leq J)$ corresponds to the following state-space representation:

$$\begin{aligned}\mathbf{x}_{k+1}^{(j)} &= \mathbf{A}\,\mathbf{x}_k^{(j)} + \overline{\mathbf{w}_k} \\ \mathbf{y}_k^{(ref,j)} &= \mathbf{C}^{(ref)}\,\mathbf{x}_k^{(j)} \\ \mathbf{y}_k^{(j)} &= \mathbf{C}^{(j)}\,\mathbf{x}_k^{(j)}\end{aligned} \tag{13}$$

with one system-matrix $\mathbf{A}$ (identical for all records because the same mechanical system is measured), a fixed output-matrix $\mathbf{C}^{(ref)}$ (identical for all records because the reference sensor group has identical sensor locations at all records) and a specific output-matrix $\mathbf{C}^{(j)}$ for each record.

In equation (5) it was shown that the correlation function with the discrete state-space parameters $\mathbf{C}$, $\mathbf{A}$ and $\mathbf{M}$ can be represented. This equation applies only with ideal white noise at the input of the system. These conditions cannot be kept at practical measurements . Therefore the

excitation energy will be different at sequential records. For each record $j$ there exist another matrix $\mathbf{M}$. Furthermore the matrix $\mathbf{C}$ depends on the record $j$.
If you proceeds first from measurements with ideal stationary excitation, then the covariance functions will be independent of the record $j$. For this ideal case a constant right factor $\mathbf{M}$ results and the markov parameters can be written as follows:

$$\begin{aligned} \mathbf{R}_{\mathbf{yy}}^{(ref,j)} &= \mathbf{C}^{(ref)}\ \mathbf{A}^{k-1}\ \mathbf{M} \\ \mathbf{R}_{\mathbf{yy}}^{(j)} &= \mathbf{C}^{(j)}\ \mathbf{A}^{k-1}\ \mathbf{M} \end{aligned} \tag{14}$$

Since $\mathbf{C}^{(ref)}$ is identical at all records j, also $\mathbf{R}_{\mathbf{yy}}^{(ref,j)}$ will be independent of $j$. With the following block column vector

$$\mathbf{R}_{\mathbf{yy}}^{\pi} = \begin{pmatrix} \mathbf{R}_{\mathbf{yy}}^{(ref,1)} \\ \mathbf{R}_{\mathbf{yy}}^{(1)} \\ \vdots \\ \mathbf{R}_{\mathbf{yy}}^{(J)} \end{pmatrix} = \mathbf{C}\ \mathbf{A}^{k-1}\ \mathbf{M} \qquad with \qquad \mathbf{C} = \begin{pmatrix} \mathbf{C}^{(ref)} \\ \mathbf{C}^{(1)} \\ \vdots \\ \mathbf{C}^{(J)} \end{pmatrix} \tag{15}$$

it is possible to arrange a Hankel matrix $\mathbf{H}^{\pi} = Hankel(\mathbf{R}_{\mathbf{yy}}^{\pi})$. This Hankel matrix can be split into an observability matrix $\mathbf{\Gamma}$ and a controllability matrix $\mathbf{Q}$ by singular value decompostion.
As opposed to ideally stationary excitation the power of the excitation will be dependent on record with real measurements in general because of the finite recording time. So the excitation on the input of the system will not be white process and the covariance functions of the reference sensors are likewise dependent on the record $j$ for this case. The Markov parameters arise now as follows

$$\mathbf{R}_{\mathbf{yy}}^{(ref,j)} = \mathbf{C}^{(ref)}\ \mathbf{A}^{k-1}\ \mathbf{M}^{(j)} \tag{16}$$

$$\mathbf{R}_{\mathbf{yy}}^{(j)} = \mathbf{C}^{(j)}\ \mathbf{A}^{k-1}\ \mathbf{M}^{(j)} \tag{17}$$

and the construction of a Hankel matrix $\mathbf{H}^{\pi}$is not possible. The correlation functions must be standardized suitably on a uniform excitation level so that the procedure can be used further. To find a suitable standardisation, it is distinguished between reference sensors and movable sensors.

**Reference Sensors:** Further on top it was already held on that $\mathbf{C}^{(ref)}$ is regardless of record $j$, because the locations of the reference sensors are fixed with all records. If you defines a block-line vector:

$$\mathbf{R}_{\mathbf{yy}}^{(\mathbf{ref})} = \begin{pmatrix} \mathbf{R}_{\mathbf{yy}}^{(\mathbf{ref},\mathbf{1})} & \mathbf{R}_{\mathbf{yy}}^{(\mathbf{ref},\mathbf{2})} & \cdots & \mathbf{R}_{\mathbf{yy}}^{(\mathbf{ref},\mathbf{J})} \end{pmatrix} \tag{18}$$

then arises:

$$\mathbf{R}_{\mathbf{yy}}^{(\mathbf{ref})} = \mathbf{C}^{(ref)}\ \mathbf{A}^{k-1}\ \mathbf{M} \quad \text{mit} \quad \mathbf{M} = \begin{pmatrix} \mathbf{M}^{(1)}\ \mathbf{M}^{(2)}\ \cdots \mathbf{M}^{(J)} \end{pmatrix} \tag{19}$$

From $\mathbf{R}_{\mathbf{yy}}^{(\mathbf{ref})}$ a Hankel matrix can be built up which can be split with singular value decomposition in the observability matrix $\mathbf{\Gamma}$ and the controllability matrix $\mathbf{Q}$.

$$\mathbf{H}^{(\mathbf{ref})} = Hankel(\mathbf{R}_{\mathbf{yy}}^{(\mathbf{ref})}) = \mathbf{\Gamma}\mathbf{Q} \tag{20}$$

From the matrix $\mathbf{Q}$ the record depending matrices $\mathbf{Q}^{(1)}$ to $\mathbf{Q}^{(J)}$ can be extracted column by column.

$$\mathbf{Q} = \left(\left[\mathbf{q}_a^{(1)}\mathbf{q}_a^{(2)}\dots\mathbf{q}_a^{(J)}\right]\left[\mathbf{q}_b^{(1)}\mathbf{q}_b^{(2)}\dots\mathbf{q}_b^{(J)}\right]\dots\left[\mathbf{q}_n^{(1)}\mathbf{q}_n^{(2)}\dots\mathbf{q}_n^{(J)}\right]\right) \tag{21}$$

$$\mathbf{Q}^{(1)} = \left(\mathbf{q}_a^{(1)}\mathbf{q}_b^{(1)}\dots\mathbf{q}_n^{(1)}\right) \quad \text{etc.} \tag{22}$$

These controllability matrices $\mathbf{Q}^{(j)}$ contain beside the system matrix $\mathbf{A}$ (identical with all records $j$) only the parameter $\mathbf{M}$ depending from $j$. These matrices $\mathbf{Q}^{(j)}$ are the base to norm the correlation functions of the movable sensors to a uniform excitation level as in the following paragraph described.

**Moving Sensors** According to equation (17) are the Hankel matrices built up from the correlation functions of the moving sensors depending on the excitation of the record:

$$\mathbf{H}^{(j)} = Hankel(\mathbf{R}_{\mathbf{yy}}^{(j)}) = \mathbf{\Gamma}^{(j)}\mathbf{Q}^{(j)} \tag{23}$$

To compute Hankel matrices which correspond to a uniform excitation, the Hankel matrices $\mathbf{H}^{(j)}$ are multiplied by a standardisation factor which results from the controllability matrices $\mathbf{Q}^{(j)}$:

$$\overline{\mathbf{H}^{(j)}} = \mathbf{H}^{(j)}\left(\mathbf{Q}^{(j)T}\left[\mathbf{Q}^{(j)}\mathbf{Q}^{(j)T}\right]^{-1}\mathbf{Q}^{(1)}\right) \tag{24}$$

These standardized Hankel matrices contain the following markov parameters:

$$\overline{\mathbf{R}_{\mathbf{yy}}^{(\mathbf{j})}} = \mathbf{C}^{(\mathbf{j})}\ \mathbf{A}^{\mathbf{k-1}}\ \mathbf{M}^{(\mathbf{1})} \tag{25}$$

If the following block-column vector is defined now,

$$\overline{\mathbf{R}_{\mathbf{yy}}} = \begin{pmatrix} \mathbf{R}_{\mathbf{yy}}^{(ref,1)} \\ \overline{\mathbf{R}_{\mathbf{yy}}^{(\mathbf{1})}} \\ \vdots \\ \overline{\mathbf{R}_{\mathbf{yy}}^{(\mathbf{J})}} \end{pmatrix} = \mathbf{C}\ \mathbf{A}^{\mathbf{k-1}}\ \mathbf{M}_{\mathbf{1}} \tag{26}$$

it is possible to built up a Hankel matrix $\overline{\mathbf{H}}$ that contains the data of the reference sensors as well as the data of the moving sensors of all records $j$.

$$\overline{\mathbf{H}} = Hankel(\overline{\mathbf{R}_{\mathbf{yy}}}) = \mathbf{\Gamma}\mathbf{Q} \tag{27}$$

This Hankel matrix $\overline{\mathbf{H}}$ can be split by singular value decomposition in the parts $\mathbf{\Gamma}$ and $\mathbf{Q}$. From it the state space parameters $\mathbf{C}$, $\mathbf{A}$ and $\mathbf{M}$ let themselves determine in analogy to the output-only method with fixed sensor order. You receive a local-discrete model which is arbitrarily detailed, dependent from the number of the movable sensors and the number of records.

## 3 VIBRATION MEASUREMENTS AT A TIED-ARCH BRIDGE

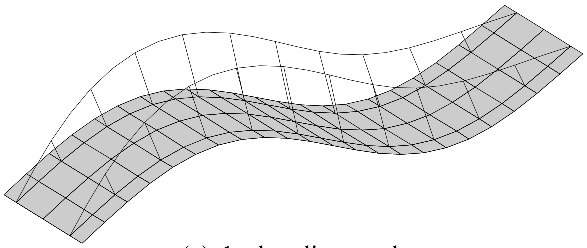
In Hünxe (Germany) a tied-arch bridge with a span of 62.5m (Fig. 1) was deconstructed in 2005 because of corrosion. The bridge was built in 1952 in order to lead the country road no. 463 across the Wesel-Datteln-Canal. Main- and cross-girder, track-slab and the hanger consisted of prestressed concrete, the arch was built in reinforced concrete. On the verge of

Figure 1: bridge near Hünxe in Germany (span: 62.5m)

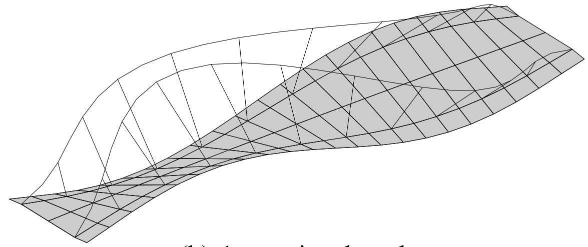
deconstruction it was possible to accomplish numerous vibration measurements. For the experiments two damaged states were induced. First an additional support near the bridge bearing of one main girder was set-up. In a second experiment one hanger from one tied arch was cut through. For the different experiments the bridge was excited through deterministic (by impulse hammer) and stochastic (by traffic, wind, etc.) loads. The available measurement system could handle sixteen acceleration sensors. Only the vertical acceleration of the two main girders were measured. For the output-only method the position of the sensors were fixed. For the polyreference setup the sensors were split into two groups: Six sensors with fixed position (reference-group) and ten sensors with changing position (moving group). With this setup four records with different sensors locations were accomplished. So models with 46 DOF (4 records * 10 moving sensors + 6 reference sensors) could be formed by the polyreference method. Additional records would have been possible to increase the resolution of the model.
To check the plausibility of the measuring results a finite element model was provided. Main-girder, cross girder and arch were modeled by bernoulli elements, the track-slab was modeled by linear shell elements. In figure 2 a 3-dimensional view of the first bending and torsional mode of the model is shown exemplarily. Afterwards the finite element model could be adapted to the measuring results. Now a model with realistic behavior is available to test new algorithm for identification while future research.

### 3.1 System variation through cut Hanger

Before the deconstruction of the bridge took place one of the twenty hangers was cut through. The third hanger on south-west side was selected because of static rules for the following deconstrutction of the whole bridge. The cross-section of the prestressed concrete hanger varies over the height from about 55x50cm down to 35x30cm upside. After this induced damage vibration



(a) 1st bending mode



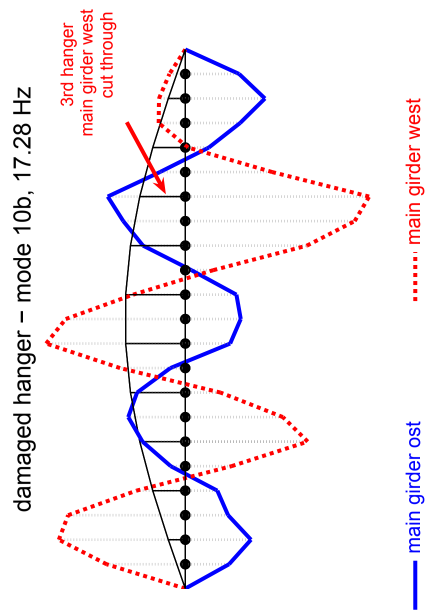
(b) 1st torsional mode

Figure 2: finite-element-model: reference-system

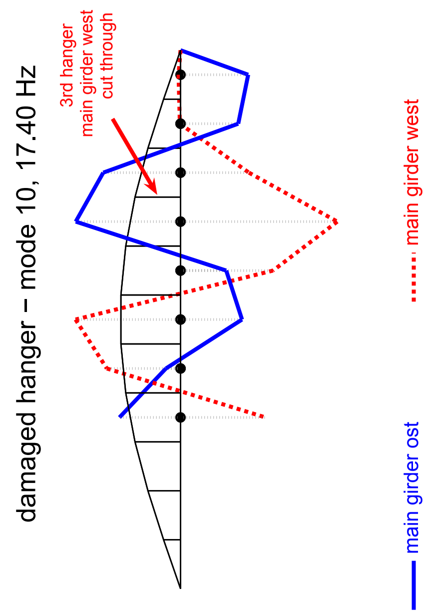
measurements with deterministic (impulse) and stochastic (traffic, wind) excitation took place analogously to the reference measurements. Afterwards the black-box models was identified with the described subspace method. Within the future research these black-box models are to be transferred into physically interpretable white-box models. Then direct statements about damage will be possible.

Figure 3: system modification: hanger cut through

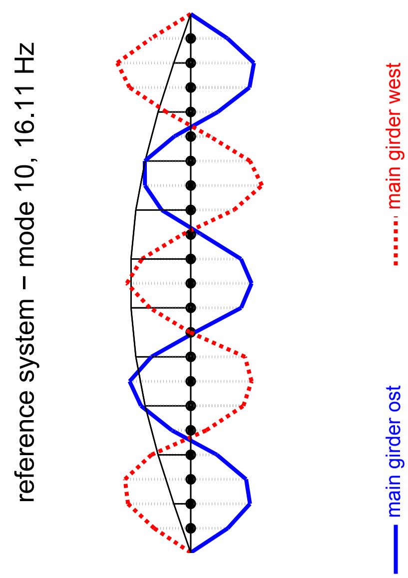
In this article the modes should be shown as first step for damage localization. At the example of the 10th mode it is possible to see the change of the system by the generated damage as well as the advantage of higher detailed models. In figure 4 a comparison occurs between polyreference method and output-only with fixed sensor positioning. The difference of information is substantial for this example. The modes changed by the damage are shown in figure 5. After the failure of the hanger two global torsional modes (5 maxima) can be identified with frequency clearly changed in each case. The modes have their biggest change of amplitude in the area of the damage. The same results were achieved by the finite element method.



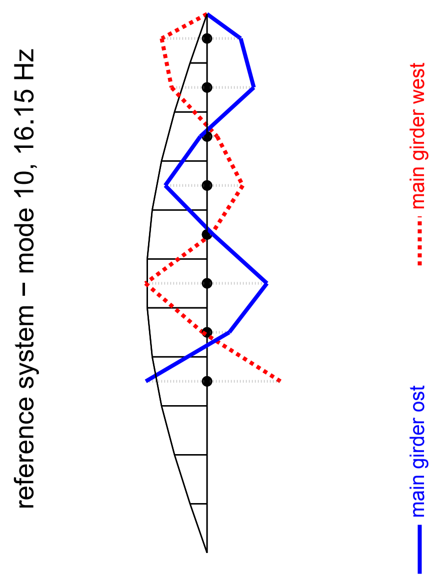

(a) damaged hanger - polyreference




(b) damaged hanger - fixed sensors

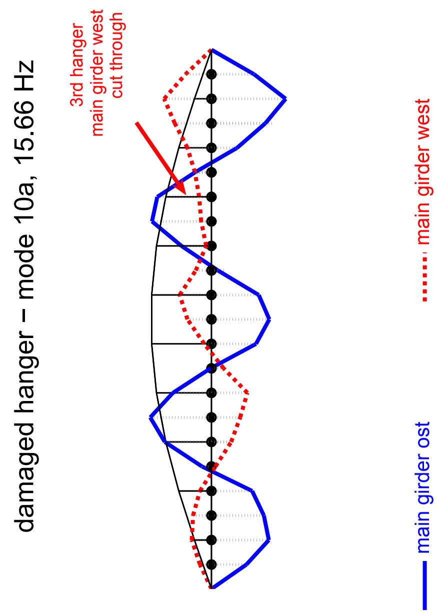



(c) reference system - polyreference

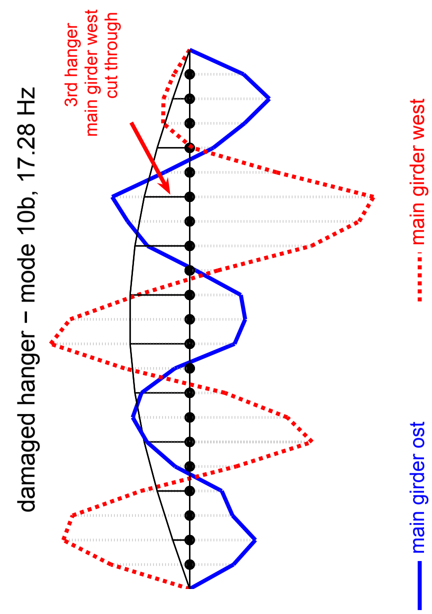



(d) reference system - fixed sensors

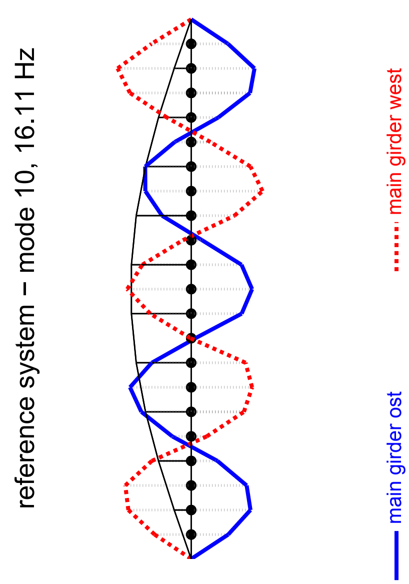
Figure 4: Comparison between polyreference method and output-only method with fixed sensor locations




(a) damaged hanger - mode 10a




(b) damaged hanger - mode 10b




(c) reference system

Figure 5: torsional mode from reference system und after cut hanger

### 3.2 System Variation Through Additional Support

An additional support was set-up in order to induce an other system modification. The support was located under the western main girder in a distance of about 6 meters. It consists of a HEB steel profile and two hydraulic pressing (Fig. 6). With this configuration all measurements were

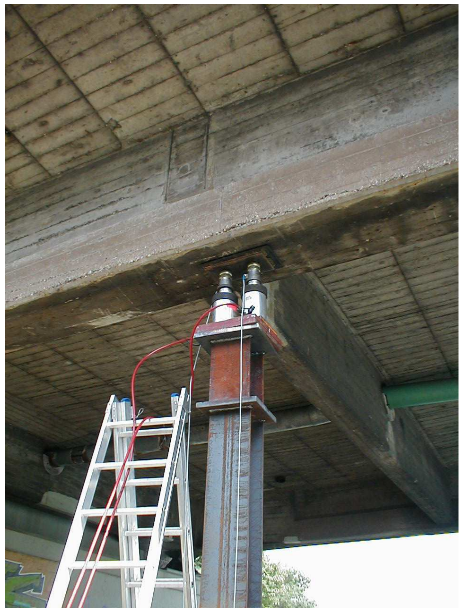


Figure 6: system variation through additional support

repeated in analogy to the reference measurements. As expected the bridge eigenfrequencies have rised because of the increased stiffness of the mechanical system. The influence is recognizable at the first mode most clearly (Fig. 7). The frequency has increased by about 10 percent, the amplitudes of the additional supported western main girder are reduced in comparison to the eastern one. Now the originally pure bending mode also has torsional parts.

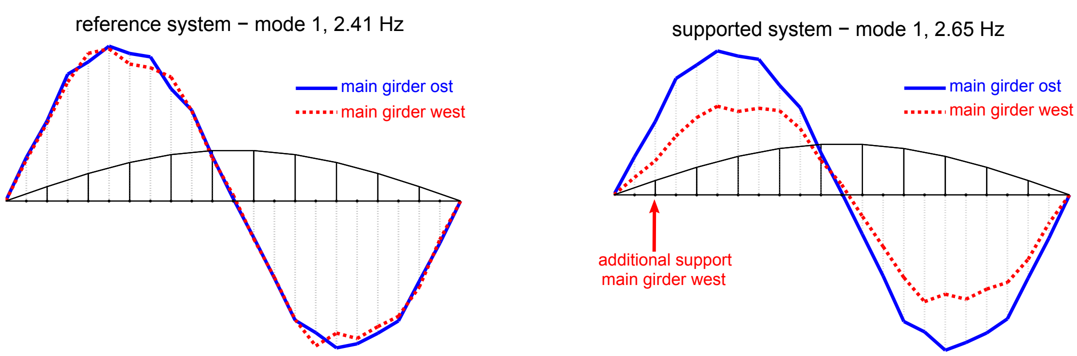



Figure 7: mode 1 - reference and supported system

## 4 SUMMARY

The stochastic system identification is able to estimate Black-Box state space models. These models can describe the transfer behavior of mechanical models. The polyreference method as add-on to output-only was introduced in detail. This method allows to identify high detailed models in spite of limited numbers of sensors. During an experimental test on a prestressed-concrete tied arch bridge the introduced procedures were used for the system identification. Two system modifications should show the potential of the algorithm to identify and locate the damages. Single modal parameters have been introduced here as the first results. The results of the polyreference method are superior to the classical procedures thereby due to the higher detailing. Nevertheless, the identified complete state space models contain additional to modal parameters the weighting function of the mechanical system. The aim of the further research is to transfer the identified black-box models in white-box models. These white-box models are physically interpretable and permit a direct damage localization.

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