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SOME PRINCIPAL REMARKS

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Abstract: Core of this contribution is the comparison of different fault detection philosophies applied to large vibrating structures. Furthermore ideas are given to overcome application problems of causal fault detection.

Key Words: Observer, Parameter Identification, Signal Analysis, Fault Detection

INTRODUCTION: Reliability and safety aspects are becoming much more important due to higher quality requirements, complicated and/or connected processes and structures. The fault detection approaches to be commonly used in machine- and rotordynamics - in general: of large vibrating structures (LVS) - are based on signal analysis methods. By this way the human knowledge of the behavior of the unfaulty system is used as a base for the comparison with the actual behavior. Applying signal analysis methods (fourier transforms, spectrums etc.) the vibrational behavior will be monitored very well, but has to be interpreted.

The signal based approaches do not use the system knowledge, especially the mechanical parameters of the structure. This available knowledge is typically used by the operating staff interpreting the resulting signal parameters.

Applying methods of modern control theory these problemes can be defused. In this contribution a principal overview about results concerning observers and estimators as methods of the modern control theory will be given. In this context the aim of those approaches is to observe the system behavior, and to detect system changes.

In the last years several methods of modern control theory are specified and applied

- to fault detection ascertaining a failure of sensors/components/faults in/of the system,
- to fault diagnosis determining the existence of specified faults, and
- to fault isolation, which implies the separation of further effects regarded as unknown inputs with respect to the changes caused by the fault in dynamical systems and structures.

Keywords of the last decade are Residual Generator, Decision Maker, Extended Kalman Filter, Parity Equation and Diagnostic Observer /1,3,8,13,14/.

Actual developments are denoted by the consideration / the separation of the influence of modeling errors which includes disturbance decoupling /8/, and also aspects of causal - based fault diagnosis, i.e. the assignment physical fault - monitoring parameter.

Applying signal analysis methods, fault detection leads to the comparison of actual signal values with old values of ordinary behavior, or the comparison to maximum allowed values. These strategies are based on pattern recognition methods. Pattern recognition methods can be applied to compare the effects of the faults found in various experiments

or simulations to those resulting from the considered system.
The mentioned developments are characterized by some indirect assumptions and restrictions which should be noted here: The standard methods of fault detection allow the information condensation of the measurable dynamical behavior to some characteristic values, which are observed. This only implies the use of the outputs of the system. Information about structure and parameter and also of the inputs of the system are not used.

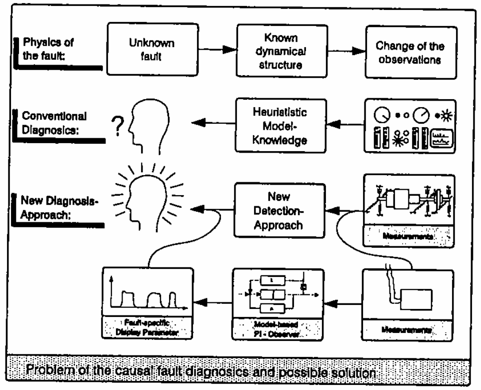

Fig. 1: Procedure of the human fault reasoning process
In fact this contains only a phenomenological study of the system using directly available measurements. Different faults are assumend by different signatures of the characteristic values, but this does not include a causal analysis of the fault or the change itself. The relation between the parameters determined by signal analysis and the physical fault is established by the knowledge and experience of the machine operator, but it should be noted, that this relation often is not unique, but solved by the operators in various practical situations.
The typical reasoning process is given in fig. 1. The experiences are collected as results by doing simulations and experiments, cf. first row. Here starting with given boundary and initial conditions, determined system changes lead to typical results, like signatures. The fault reasoning process turns this direction back. From the observed phenomena it is concluded to the supposed causal reason.
On the other hand several properties of the mentioned strategy make the 'human-decision-making process' itself difficult:

- The relation between the phenomena given by the measurements and the fault is ambiguous, so the results of signal analysis have to be interpreted. Especially in the case of methods, which are not close (enough) to the process itself, the area of possible interpreting errors is wide and depends on the individual human.
- Economical and psychological aspects determine the situation in which the operators have to decide. Proving the existence of a shaft crack by stopping the turbine of a power plant e.g., is a costly procedure. If the non-existence of a crack is definitly obtained, this increases the sensibility for the next decision situation, where the problem appears again.

- Especially in the case of rare faults with high dangerous potential (in atomic power plants or in chemical industry) this 'human decision making process' is very difficult and critical. As a result of these experiences, the challenge is to apply new methods, which lead to a better inner view of the system to be observed. This can be done by applying methods, which use more information about the system itself.

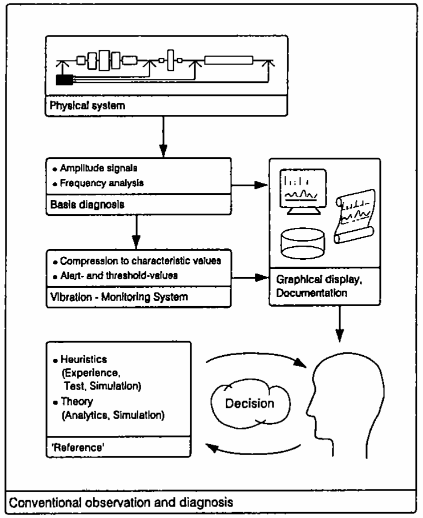

Fig. 2: Conventional observation and diagnosis
The next sections introduce the quantitative model-based approaches briefly and from a principal point of view. Details for further information can be found in the numerous literature.

ANALYTICAL REDUNDANCY METHODS - OBSERVERS: Observers are the base for an analytical redundancy approach for fault detection. Here analytical relationships describing dynamical relations (in contrast to hardware redundancy) are used for detection of changes. The assumed analytical redundant description are represented by the plant (and possibly the failure) model. The interesting criteria are the capability of the scheme concerning isolability, sensitivity and robustness.
Starting with the linear, time - invariant state space description

$$\dot{x} \;=\; Ax + Bu + E_d d_d + K_d f_d \quad y = Cx + E_m d_m + K_m f_m \tag{1}$$

with the n-dimensional state vector x, the r-dimensional input vector u, the m-dimensional output vector y, the system matrix A, the input vector B, the measurement matrix C, the distribution matrices E_d, E_m of the unknown inputs d_d and d_m acting on the dynamics d_d and the measurements d_m, the distribution matrices K_d, K_m of the fault influences f_d, f_m which are also of appropiate dimensions, the task to build up an obser-

ver using the given system description with $(A,\ C)$ - observerbility (or the observerbility of an interesting subspace) to estimate $\hat{x}$, or an interesting supspace, respectively.
Differences between observed / estimated and measured behavior expressed by the estimation error

$$e = \hat{x} - x \tag{2}$$

are used as residuals for basic FDI-concepts. The residual analysis by different strategies can be used checking occurence of faults and their location. In this concept it should be noted that the FDI-concepts devide between

- instrument fault detection ($\rightarrow$ sensor fault detection),
- component fault detection ($\rightarrow$ parts of the interconnected system) and
- actuator fault detection ($\rightarrow$ actuators as parts of systems to be controled).

In the context of fault detection schemes for application to LVS vibrating structures only the fault detection idea itself is of interest for the main task of structural and parametric change detection.
The parity space approach uses the observability relation between the measurements (done by sensors) and the mechanical system. So sensor failure leads directly to changes in the observation relations. Using some structural and logic informations a so called parity space vector can be used in finding the failure by considering the vector elements. The success of such approaches based upon a good agreement between the real (unfaulty / fault free) system and the representing model. In the non - corresponding case errors in the error equation occur and problems concerning the differentation between model error and appearing fault appear.
The development of robust residual generator, in which the generated estimations of inner states and measurements are independent of uncertainties are the goals of actual developments. Here, two research directions will be declared briefly:
Unknown Input Observer: The idea of decoupling uncertainties (caused by modeling errors) and change effects through faults from a mathematical exact approach is core of the Unknown Input Observer (UIO) or in general of the robust residual generation. Here a lot of scientific work has been done. Briefly a short introduction is given based on the papers of Frank /4,5/, where also the mathematically exact statements can be found:
Following the description in /4/ the dynamical system

$$\dot{z} \;=\; Fz + Ju + Gy \qquad r = L_1 z + L_2 y \tag{3}$$

with z the t-dimensional subspace of x and the v-dimensional subspace r of the outputs, called residual, is considered. This system is an unknown input fault detection observer of the system (1,2).
The corresponding equation for the estimation error is

$$\dot{e} \;=\; \dot{z} - T\dot{x} \tag{4}$$

$$\dot{e} \;=\; Fz + ju + GCx + GE_m d_m + GK_m f_m - TAx - TBu - TE_d d_d - TK_d f_d \tag{5}$$

with the output relation

$$t = L_1 z + L_2 Cx + L_2 E_m d_m + L_2 K_m f_m \,. \tag{6}$$

To fulfill the mentioned robustness requirements exactly, some equations have to be solved:

$$TA - FT \;=\; GC \qquad J = TB \qquad TE_d = 0 \tag{7}$$

$$GE_m \;=\; 0 \qquad L_2 E_m = 0 \qquad L_1 T + L_2 C = 0 \,. \tag{8}$$

The error dynamics of the residual results as

$$\dot{e} \;=\; Fe + GK_m f_m - TK_d f_d \qquad r = L_1 e + L_2 K_m f_m \,. \tag{9}$$

The conditions therefore are

$$\text{Rank}\,[TK_d] \;=\; \text{Rank}\,[K_d] \quad \text{and} \quad \text{Rank}\left[\begin{pmatrix} G \\ L_2 \end{pmatrix} K_m \right] \;=\; \text{Rank}\,[K_m] \tag{10}$$

as formulated in (Frank, 1993). In many practical cases these conditions can not be fulfilled. To solve the design procedure to fulfill eqn. (9-14), methods are given in /23/ using the Kronecker canonical representation, in /12/ using the eigenstructure assignment approach. New results are given in /9,10/. The main problem for application to LVS is concerned with the strong assumption that distinguishing p faults and q unknown inputs p+q independent measurements are needed /5/. Because of the large number of modeled elastic degrees of freedom this requirements often can not be fulfilled.

Proportional Intergral Observer: The second approach to be introduced is the PI-observer, as an approximate procedure for decoupling uncertainties and faults. Here the decoupling results not from the observer design itself (as with the UIO), but from the high observer gains. The idea is presented in /21/ and applicated to FDI of mechanical schemes in general /22/.
Assuming that the system with unknown inputs (faults, modeling errors, further external disturbances) is described by

$$\dot{x} \;=\; A_o x + Bu + \Delta A(x,u,t)x = A_o x + Bu + \tilde{N}\tilde{f} \quad , \tag{11}$$

where A_o describes the unfaulty, nominal system, and $\Delta A(x,u,t)$ (Eq. (19)) describes the influences of system changes due to faults and additional inputs due to external disturbances etc. . Here $\tilde{N}$ in Eq. (20) includes all the external effects acting on the nominal system and is of full rank. If the system (20) is observable and some conditions concerning the number of independent measurements r_1 = rank C, then there exists a PI-Observer introduced in /21/, which estimates the unknown inputs in r_2 input channels. The basic idea of the Proportional Integral Observer (PIO) is to extend the usual Luenberger observer with some degrees of freedom. These degress of freedom are used for the estimations of the unknown inputs and are driven by the integral of the estimation error of the measurements.
Then the idea is that the additional inputs can be divided by

$$\Delta A(x,u,t)x = \tilde{N}\tilde{n} = Nf + N_c f_c \tag{12}$$

where N selects the interesting input channels for the unknown inputs f to be estimated, considering dynamical effects of faults, located to desired inputs selected by N similar to the matrices E_d, K_d of the UIO.
The product $N_c f_c$ describes the remaining inputs of the other input channels. With

$$rank\,N = r_2 \leq rank\,C = r_1 \,, \tag{13}$$

applying high gains, this technique is easy to understand.
With $\begin{bmatrix} L_1 \\ L_2 \end{bmatrix} = \rho_1 \begin{bmatrix} \tilde{L}_1 \\ \tilde{L}_2 \end{bmatrix}$ an extended error equation can be written as

$$\frac{1}{\rho_1}\begin{bmatrix} \dot{e} \\ \dot{\hat{f}} \end{bmatrix} = \frac{1}{\rho_1}\begin{bmatrix} A & N \\ 0 & 0 \end{bmatrix}\begin{bmatrix} e \\ \hat{f} \end{bmatrix} - \begin{bmatrix} \tilde{L}_1 \\ \tilde{L}_2 \end{bmatrix} Ce - \frac{1}{\rho_1}\begin{bmatrix} N \\ 0 \end{bmatrix} f - \frac{1}{\rho_1}\begin{bmatrix} N_c \\ 0 \end{bmatrix} f_c \quad .$$

From eq. (23) it follows that

$$Ce = 0 \tag{14}$$

for $\rho_1 \to \infty$. Differentiating eq. (23) and using (24) gives

$$C\dot{e} = C(A - L_1 C)e + CN(\hat{f} - f) + CN_c(\hat{f} - f_c) \quad . \tag{15}$$

Assuming

$$CN \ = \ 0 \tag{16}$$

and eq. (24) it can be seen that

$$CAe = 0 \quad . \tag{17}$$

In the same way assuming the observerbility of the complete system it is obtained

$$CA^{\mathrm{i}}e = 0 \quad \mathrm{i} = 0, 1, ..., \mathrm{k} - 1 \quad . \tag{18}$$

Then from (24), (26) and (27) it follows that

$$e = 0 \tag{19}$$

due a rank condition related to the assumption of the observability. Substituting (29) into (23) gives with $\rho_1 \ \to \ \infty$

$$0 = N\hat{f} - Nf - N_c f_c \quad . \tag{20}$$

With $N = \rho_2 \tilde{N}, \quad \rho_2 \to \infty$ eq. (30) gives

$$\hat{f} - f = 0 \quad , \tag{21}$$

i.e. the estimates $\hat{x}$ and $\hat{f}$ of the PIO (12) converge to the system states and the unknown inputs f desired by the matrix N. This result is obtained in presence of other unknown inputs in all remaining states when ρ_1 and ρ_2 tends to infinity. The complete proof is given in /22/. This short introduction shows that the application of the PIO is similar to the application of an UIO for fault detection and isolation in the presence of modeling errors etc. . The conditions for applications are weaker then those of the UIO. Related to the LVS the conditions can be easily fulfilled. The main restrictions are that only displacements (instead of velocities) can be used (eq. 26) and the assumptions given by eq. (22). Related to the practical demand of causal fault detection both approaches have the problem for application of multiplicative faults.

PARAMETER ESTIMATION APPROACHES: Parameter estimation approaches also use the input-output relation modeled by difference- oder differential equations using a set Θ of parameters a_i, b_i for the input - output relation

$$y(k) + ... + a_n y(k-n) = b_0 u(k) + b_1 u(k-1) + ... + b_m u(k-m) \tag{22}$$

as a scalar difference equation (or a set of equations) between the output y and the input u, with k as the actual discrete time step.
The parameters a_i, b_i do not typically represent the physical parameters p_i of the system, but if the relation

$$\Theta = f(p_i) \tag{23}$$

is unique, an inverse transformation f^{-1} gives the physical parameters. In /15/ a fast backtransformation approach is introduced.
Changes of the physical system are assumed as changes Δp_i, which lead also to changes of the process coefficients a_i, b_i. The idea of FDI using parameter estimation and identification approaches is to observe the parameters (process or physical parameters) using threshold values, some heuristic methods inspired from practice or stochastic decision theory. For solving the estimation process a lot of estimation techniques are available like least squares (LS) or recursive least squares (RLS) techniques. Important is that the assumptions concerning the available measurements φ are

$$det \ E\{\varphi(\mathrm{t})\varphi(\mathrm{t})^T\} \ \neq \ 0 \, . \tag{24}$$

This includes a high information level concerning the measurements of the system. This can be easily be fulfilled in many practical cases beside elastic structures. Here due to the high number of modeled elastic degrees of freedom this assumption is hard to fulfill. For every degree of freedom (dof) an independent measurement is needed.
Furthermore the robustness properties are similar to observer based methods. Here the structure of the input - output relation (concerning order, linearity, characterics of nonlinearity) also has to be known. An implicit assumption is, that the structure of the system (represented by the structure of difference- /differential equation(s)) does not change due to the fault. One way to overcome these difficulties is to consider only the modal characteristics (Basseville et al., 1993b). It should be noted, that this idea is based on a linear approach (modal characteristics, eigenfrequencies, eigenvectors).

COMBINED APPROACHES: Using the (nonlinear / linear) Extended Kalman Filter /11,17/ for the dynamical model extension of the unfaulty system, a fault model is used, which has to be parametrized. If the nominal system is not exactly known, the same problems as mentioned with analytical redundancy methods appear: faults and modeling errors has to be decoupled. The idea of modeling the fault implies furthermore the more difficult problem to assume the structure and the order of the mechanical description of the fault (same assumptions as for parameter estimations approaches).
In spite of the mentioned assumptions this approach has also been successfully applied to many practical mechanical problems. As example the work of Seibold /19,20/ is mentioned. Here some approaches for crack detection of a rotor, using only the measurements of the bearings, are compared.
The idea of combining the Extended Kalman Filter approach with an unstructured extension (as an integral feedback like the PI-observer approach) is firstly given in /18/ and is called 'Modified Extended Kalman Filter' (MEKF).
In the case that the nominal system (which is the base building up the Kalman Filter) also is not known, a combination of Kalman filtering and parameter identification techniques can be used /6,7/. In this way an adaptive fault detection approach is established, which

avoids problems of modeling errors in a certain way. On the other hand systems changes due to faults can also be adapted as modeling errors.

CRITICAL REMARKS: The most FDI-schemes and approaches have significant advantages concerning special related problems /14/. Several conferences like SAFEPROCESS focus the community to this application field of observers / filters and identifiers. In this contribution the interest is focussed to the application of fault detection schemes to (mechanical) LVS. Fault detection of vibrating structures implies that only the measurements of the vibrating structures can be used beside the system / model information itself.

Technique \ Criteria	1	2	3	4	5	6	7
UIO	+	-	+	+	--	o	+
PIO	+	o	+	+	+	o	+
Parity	+	+	+	+	+	o	+
EKF	+	++	++	+	+	--	+
PIA	+	o	-	o	--	o	++
Combined PIA + EKF	-	+	o	o	+	o	o
Signal based approaches	++	-	-	--	++	++	++

Comparison of FDI-Approaches concerning large vibrating structures

Fig. 3: Comparison table of FDI-approaches used for LVS
(Notation: ++ : very good, + : good, o : average, – : very bad, - : bad)

Considerung the advanced fault detection problems of large vibrating structures (examples: cracks in rotating machinery, wings of large aircrafts; changes of space truss structures) the following criteria can be build up:
1. Suitability for On-line-use, **2.** Uniqueness of the relation: System changes - Monitored parameter, **3.** Vicinity of the observed parameter to the interesting, physical problem, **4.** Effort to conclude from the monitored parameter to the physical change, **5.** Expenditure for the necessary measurements, **6.** Exactness of necessary system information and **7.** Practicability concerning the realisation in situ
• Considering criteria 1 (On-line use) the signal-based approaches are the fastest ones, the other approaches are realizable, the combined approach has an additional inner dynamics which needs time.
• Considering criteria 2 (Uniqueness) the Extended Kalman Filter is the best because of the included fault model (costs: criteria 6). Negative results are possible if the output is ambigiuos related to the faults.
• As criteria 3 the vicinity of the outputs to the faults is valuated. If a model is used for

the FDI-approach (like EKF) this leads to good results (costs: criteria 6), if the parameters are unrelated to faults this is negative.
• Considering criteria 4 (Conclusion effort) the EKF get (++) notation, bacause if a model is available for the fault there is nothing to conclude; signal based approaches get (-) notation because the effort depends on the knowledge of the interpreter.
• Considering criteria 5 (Expenditure for the measurements) (++) notation is given if the measurements are easy to realize (signal based approaches) or (–) notation if this is difficult.
• Criteria 6 judges the exactness of the necessary model information (system and fault) for successful application. The EKF get (–) notation because of using typically unknown but necessary fault model, the signal-based approaches get (++) notation because no model is needed (costs: criteria 4).
• Criteria 7 (Practicability of the algorithm itself) judges the effort for the practical engineer to apply and handle the considered approach. If nothing has to be done (++) notation is given, if the algorithm is complicated, needs corrects starting values etc. (o) notation is given.
All of the approaches have advantages and disadvantages. This is obvious comparing EKF and signal-based approaches. The output of EKF is clear, unambigious and unique but strongly model-dependent. The output of signal-based approaches is not unique and has to be interpreted but the application is simple.
The combined parameter identification + EKF approach is not useful because of the adaptation. The PIA can also adapt the fault, if the fault model of EKF is not exact known.

WHAT HAS TO BE DONE IN FDI FOR LVS? The comparison of the different approaches applied to large vibrating structures in fig. 3 shows:
• Approaches easy to apply (criteria 1,5,6,7) (→ Signal-based approaches) have disadvantages concerning to the causality assignment (criteria 2,3,4). To overcome these disadvantages such approaches can be combined with knowledge based techniques like expert systems, but it should be noted that the principal problems depicted in fig. 2 make it difficult to solve the causality requirements for every fault problem (criteria 2,4). This is mainly due to the (for this case poor) information level of the measurements.
• Approaches with an 'easy-to-understand-output' (→ EKF, Parity space approach) (criteria 2,3,4) have disadvantages concerning the assumptions related to the necessary system and fault model information. To overcome these disadvantages the assumption of the knowledge of the fault model has to be canceled. A first approach is done in the work of Seibold et al. (Seibold, Söffker, Fritzen, 1993b). In this case the extension of the EKF is unstructured. Applied to mechanical systems forces and/or torques are estimated. This modified EKF and the PIO are identical, beside the fact that there exist different techniques for the design procedure of EKF.
• From a theoretical point of view, the ideal candidate for FDI-applications seems to be the UIO. Here the principal problem (of quantitative model based approaches) to devide model uncertainties and faults is solved by a mathematical exact approach. The costs for the exact solution can not be payed for the application to LVS; the measurements are not available in practice.
• The same problem is connected to the application of the parameter identification approach (PIA) for advanced purposes. These techniques have their legitimation from

structural testing (of new structures etc.). For online-use during the life-time of the system the measurement effort is high or can not be fulfilled (criteria 5). The causal relation is principally not given by the parameter (a_i, b_i). To overcome these difficulties fast backtransformation techniques have to be developed to observe physical parameters.
• The application of the PIO is system-model dependent, but fault model independent, the measurement effort is low, the display parameters using the PIO-technique itself /21/ are mechanical states which has to be interpreted. To overcome these interpretation leakage with the goal to be closer to the physics of the fault, in /22/ a hypothesis testing strategy is suggested. Here the physical character of the fault can be displayed directly. Actual work is done to combine the testing strategy with pattern recognition qualities of neural networks /16/.
• As a provisional result it can be stated, that some research directions try to solve FDI problems related to the application to LVS. All approaches have advantages and disadvantages related to the interesting field. Actual developments try to overcome these difficulties. • To get a good base for the comparison of different techniques, a typical example should be formulated as a benchmark problem.

SUMMARY AND CONCLUSIONS: In this contribution the basic ideas of quantitative model - based fault detection and isolation are introduced and compared with practical proved and often implemented signal-based approaches. Concerning the interesting field of large vibrating structures some criteria are formulated for comparison of the techniques. As a result it can be stated that some techniques (Unknown Input Observer, Combined Parameter Identification - Extended Kalman Filter approach) are not problem adequate, other techniques (Parameter Identification Approaches, Signal-based approaches) can be applied, but do not solve the usefull causal relation in a adequate way. The remaining techniques to be considered (Proportional Integral Observer, Extended Kalman Filter, Parity Space Approach) can be applied, but have to be optimized to reach the causal relation: display parameter - physical fault. Further research work has to be done. For better comparison, a well-chosen problem adequate benchmark example should be chosen.

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