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Model-based fault-detection and diagnosis – status and applications☆

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Abstract

For the improvement of reliability, safety and efficiency advanced methods of supervision, fault-detection and fault diagnosis become increasingly important for many technical processes. This holds especially for safety related processes like aircraft, trains, automobiles, power plants and chemical plants. The classical approaches are limit or trend checking of some measurable output variables. Because they do not give a deeper insight and usually do not allow a fault diagnosis, model-based methods of fault-detection were developed by using input and output signals and applying dynamic process models. These methods are based, e.g., on parameter estimation, parity equations or state observers. Also signal model approaches were developed. The goal is to generate several symptoms indicating the difference between nominal and faulty status. Based on different symptoms fault diagnosis procedures follow, determining the fault by applying classification or inference methods. This contribution gives a short introduction into the field and shows some applications for an actuator, a passenger car and a combustion engine.

Keywords: Fault-detection; Fault diagnosis; Supervision; Health monitoring; Parameter estimation; Parity equations; State observers; Neural networks; Classification; Inference; Diagnostic reasoning; Fuzzy logic; DC motor; Outflow valve; Lateral driving behavior; Automobile; Combustion engine

1. Introduction

Within the automatic control of technical systems, supervisory functions serve to indicate undesired or not permitted process states, and to take appropriate actions in order to maintain the operation and to avoid damage or accidents. The following functions can be distinguished:

(a) *monitoring*: measurable variables are checked with regard to tolerances, and alarms are generated for the operator;
(b) *automatic protection*: in the case of a dangerous process state, the monitoring function automatically initiates an appropriate counteraction;
(c) *supervision* with fault diagnosis: based on measured variables, features are calculated, symptoms are generated via change detection, a fault diagnosis is performed and decisions for counteractions are made.

The big advantage of the classical limit-value based supervision methods (a) and (b) is their simplicity and reliability. However, they are only able to react after a relatively large change of a feature, i.e., after either a large sudden fault or a long-lasting gradually increasing fault. In addition, an in-depth fault diagnosis is usually not possible. Therefore (c) advanced methods of supervision and fault diagnosis are needed which satisfy the following requirements:

(1) Early detection of small faults with abrupt or incipient time behavior;
(2) Diagnosis of faults in the actuator, process components or sensors;
(3) Detection of faults in closed loops;
(4) Supervision of processes in transient states.

A general survey of supervision, fault-detection and diagnosis methods is given in (Isermann, 1997). In the following model-based fault-detection methods are considered, which allow a deep insight into the process behavior.

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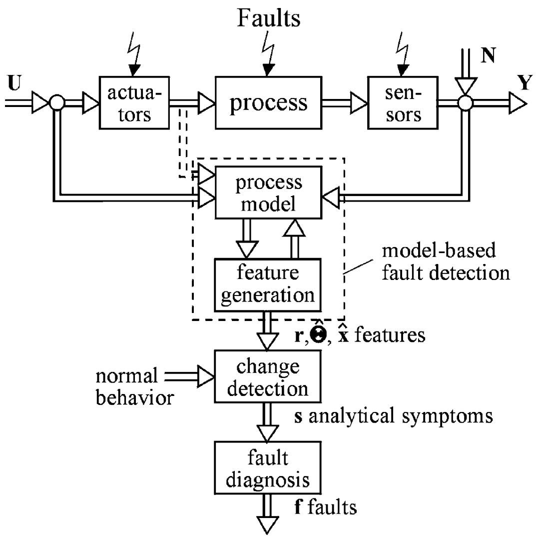


Fig. 1. General scheme of process model-based fault-detection and diagnosis.

2. Process model-based fault-detection methods

Different approaches for fault-detection using mathematical models have been developed in the last 20 years, see, e.g., (Chen & Patton, 1999; Frank, 1990; Gertler, 1998; Himmelblau, 1978; Isermann, 1984, 1997; Patton, Frank, & Clark, 2000; Willsky, 1976). The task consists of the detection of faults in the processes, actuators and sensors by using the *dependencies between different measurable signals*. These dependencies are expressed by mathematical process models. Fig. 1 shows the basic structure of model-based fault-detection. Based on measured input signals $\mathbf{U}$ and output signals $\mathbf{Y}$, the detection methods generate residuals $\mathbf{r}$, parameter estimates $\hat{\mathbf{\Theta}}$ or state estimates $\hat{\mathbf{x}}$, which are called features. By comparison with the normal features (nominal values), changes of features are detected, leading to analytical symptoms $\mathbf{s}$.

For the application of model-based fault-detection methods, the process configurations according to Fig. 2

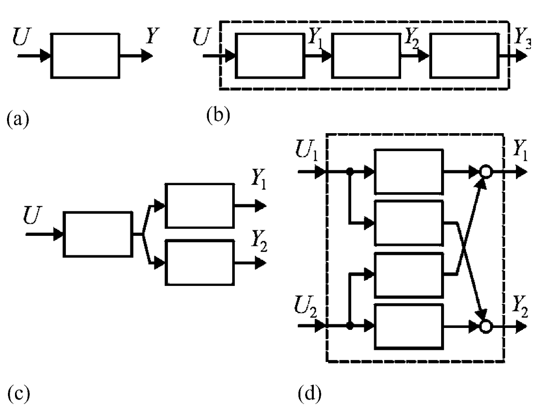


Fig. 2. Process configuration for model-based fault-detection: (a) SISO (single-input single-output); (b) SISO with intermediate measurements; (c) SIMO (single-input multi-output); (d) MIMO (multi-input multi-output).

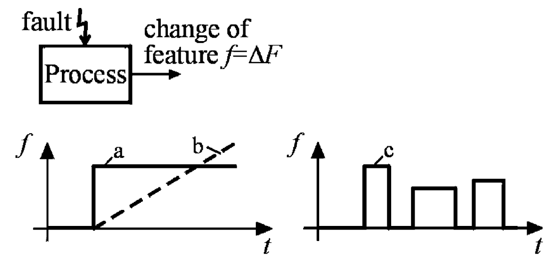


Fig. 3. Time-dependency of faults: (a) abrupt; (b) incipient; (c) intermittent.

have to be distinguished. With regard to the inherent dependencies used for fault-detection, and the possibilities for distinguishing between different faults, the situation improves greatly from case (a) to (b) or (c) or (d), by the availability of some more measurements.

2.1. Process models and fault modeling

A fault is defined as an unpermitted deviation of at least one characteristic property of a variable from an acceptable behavior. Therefore, the fault is a state that may lead to a malfunction or failure of the system. The time dependency of faults can be distinguished, as shown in Fig. 3, abrupt fault (stepwise), incipient fault (drift-like), intermittent fault. With regard to the process models, the faults can be further classified. According to Fig. 4 *additive faults* influence a variable Y by an addition of the fault f, and *multiplicative faults* by the product of another variable U with f. Additive faults appear, e.g., as offsets of sensors, whereas multiplicative faults are parameter changes within a process.

Now lumped-parameter processes are considered, which operate in open loop. The *static behavior* (steady states) is frequently expressed by a non-linear characteristic as shown in Table 1. Changes of parameters β_i can be obtained by parameter estimation with, e.g., methods of least squares, based on measurements of different input–output pairs $[Y_j, U_j]$. This method is applicable, e.g., for valves, pumps, drives, engines.

More information on the process can usually be obtained with dynamic process models. Table 2 shows the basic input/output models in form of a differential equation or a state space model as vector differential equation. Similar representations hold for non-linear processes and for multi-input multi-output processes, also in discrete-time.

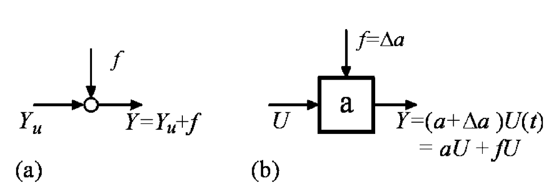
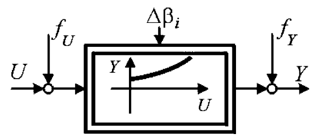


Fig. 4. Basic models of faults: (a) additive fault; (b) multiplicative faults.

Table 1
Fault-detection of a non-linear static process via parameter estimation for steady states



Measured signals: $U(t)$, $Y(t)$

Basic equation:

$$Y = \beta_0+\beta_1 U+\beta_2 U^2+\ldots+\beta_q U^q \rightarrow Y = \boldsymbol{\psi}_s^T \boldsymbol{\Theta}_s$$

$$\boldsymbol{\Theta}_s^T = [\beta_0\ \beta_1\ \ldots\ \beta_q] \quad \boldsymbol{\psi}_s^T = [1\ U\ U^2 \ldots U^q]$$

Additive faults: f_U input fault; f_Y output fault

Multiplicative faults: $\Delta\beta_i$ parameter faults

2.2. Fault-detection with parameter estimation

Process model-based methods require the knowledge of a usually dynamic process model in form of a mathematical structure and parameters. For linear processes in continuous time the models can be impulse responses (weighting functions), differential equations of frequency responses. Corresponding models for discrete-time (after sampling) are impulse responses, difference equations or z-transfer functions. For fault-detection in general differential equations or difference equations are primarily suitable. In most practical cases the process parameters are partially not known or not known at all. Then, they can be determined with parameter estimation methods by measuring input and output signals if the basic model structure is known. Table 3 shows two approaches by minimization of the equation error and the output error. The first one is linear in the parameters and allows therefore direct estimation of the parameters (least squares estimates) in non-recursive or recursive form. The second one needs numerical optimization methods and therefore iterative procedures, but may be more precise under the influence of process disturbances. The symptoms are deviations of the process parameters $\Delta\Theta$. As the process parameters $\Theta = f(\mathbf{p})$ depend on physically defined process coefficients $\mathbf{p}$ (like stiffness, damping coefficients, resistance), determination of changes $\Delta\mathbf{p}$ allows usually a deeper insight and makes fault diagnosis easier (Isermann, 1992). Parameter estimation methods operate with adaptive process models, where only the model structure is known. They usually need a dynamic process input excitation and are especially suitable for the detection of multiplicative faults.

2.3. Fault-detection with observers

If the process parameters are known, either state observers or output observers can be applied, Table 4. Fault modeling is then performed with additive faults $\mathbf{f}_L$ at the

Table 2
Linear dynamic process models and fault modeling

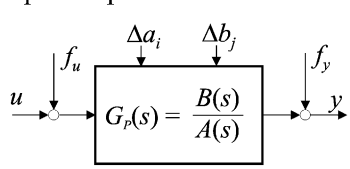
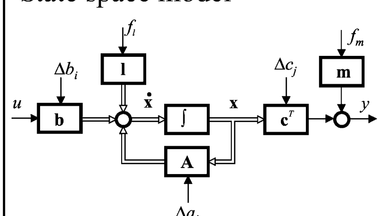
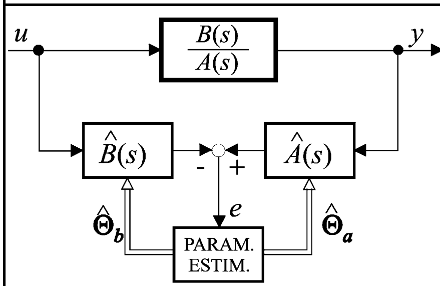
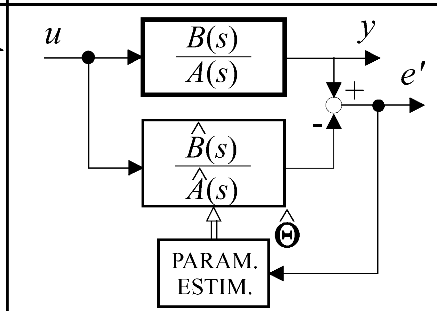
Input/output model	State space model
 Measured signals: $y(t)=Y(t)-Y_{00}$; $u(t)=U(t)-U_{00}$	
Basic equations: $y(t) + a_1 y^{(1)}(t) + \ldots + a_n y^{(n)}(t)$ $= b_0 u(t) + b_1 u^{(1)}(t) + \ldots + b_m u^{(m)}(t)$	$\dot{\mathbf{x}}(t) = \mathbf{A}\,\mathbf{x}(t) + \mathbf{b}u(t)$ $y(t) = \mathbf{c}^T\mathbf{x}(t)$
$y(t) = \boldsymbol{\psi}^T(t)\,\boldsymbol{\Theta}$ $\boldsymbol{\Theta}^T = [a_1 \ldots a_n\ b_0 \ldots b_m]$ $\mathbf{y}^T = [-y^{(1)}(t) \ldots -y^{(n)}(t)\ u(t) \ldots u^{(m)}(t)]$	$\mathbf{A} = \begin{bmatrix} 0 & 0 & \cdot & 1 \\ 0 & 1 & \cdot & -a_1 \\ 1 & 0 & \cdot & -a_2 \\ \vdots & \vdots & & \vdots \end{bmatrix}$ $\mathbf{b}^T = [\ b_0\ \ b_1\ \ \ldots\ ]$ $\mathbf{c}^T = [\ 0\ \ 0\ \ \ldots\ \ 1\ ]$
Additive faults: f_u input fault f_y output fault	f_l input or state variable fault f_m output fault
Multiplicative faults: Δa_i, Δb_j parameter faults	$\Delta\mathbf{A}$, $\Delta\mathbf{b}$, $\Delta\mathbf{c}$ parameter faults

Table 3
Fault-detection with parameter estimation methods for dynamic processes

Minimisation of equation error	Minimisation of output error
	
Loss function: $V = \Sigma\, e^2(k)$ Method: • non-recursive $\hat{\mathbf{\Theta}} = [\mathbf{\Psi}^T\mathbf{\Psi}]^{-1}\mathbf{\Psi}^T\mathbf{y}$ • recursive $\hat{\mathbf{\Theta}}(k+1) = \hat{\mathbf{\Theta}}(k) + \boldsymbol{\gamma}(k)e(k+1)$	$V = \Sigma\, e'^2(k)$ • non-recursive parameter optimization $\hat{\mathbf{\Theta}}(\nu+1) = \hat{\mathbf{\Theta}}(\nu) + \mathbf{\Gamma}(\nu)\frac{\partial V}{\partial \mathbf{\Theta}}(\nu)$
Symptoms: • model parameters $\Delta\hat{\mathbf{\Theta}}(j) = \hat{\mathbf{\Theta}}(j) - \mathbf{\Theta}_0$ • process coefficients $\hat{\mathbf{p}} = f^{-1}[\mathbf{\Theta}]$ $\Delta\mathbf{p}(j) = \hat{\mathbf{p}}(j) - \mathbf{p}_0$	

input (additive actuator or process faults) and $\mathbf{f}_\mathrm{M}$ at the output (sensor offset faults).

2.3.1. State observers

The classical state observer can be applied if the faults can be modeled as state variable changes $\Delta\mathbf{x}_i$ as, e.g., for leaks. In the case of *multi-output processes* special arrangements of observers were proposed:

2.3.1.1. Dedicated observers for multi-output processes. Observer, excited by one output. One observer is driven by one sensor output. The other outputs $\mathbf{y}$ are reconstructed and compared with measured outputs $\mathbf{y}$. This allows the detection of single sensor faults (Clark, 1978).

Bank of observers, excited by all outputs. Several state observers are designed for a definite fault signal and detected by a hypothesis test (Willsky, 1976).

Bank of observers, excited by single outputs. Several observers for single sensor outputs are used. The estimated outputs $\mathbf{y}$ are compared with the measured outputs $\mathbf{y}$. This allows the detection of multiple sensor faults (Clark, 1978) (dedicated observer scheme).

Bank of observers, excited by all outputs except one. As before, but each observer is excited by all outputs except one sensor output which is supervised (Frank, 1987).

2.3.1.2. Fault-detection filters (fault-sensitive filters) for multi-output processes. The feedback $\mathbf{H}$ of the state observer is chosen so that particular fault signals $\mathbf{f}_\mathrm{L}(t)$ change in a definite direction and fault signals $\mathbf{f}_\mathrm{M}(t)$ in a definite plane (Beard, 1971; Jones, 1973).

2.3.2. Output observers

Another possibility is the use of output observers (or unknown input observers) if the reconstruction of the state variables $\mathbf{x}(t)$ is not of interest. A linear transformation then leads to new state variables $\boldsymbol{\xi}(t)$. The residuals $\mathbf{r}(t)$ can be designed such that they are independent of the unknown inputs $\mathbf{v}(t)$, and of the state by special determination of the matrices $\mathbf{C}_\xi$ and $\mathbf{T}_2$. The residuals then depend only on the additive faults $\mathbf{f}_\mathrm{L}(t)$ and $\mathbf{f}_\mathrm{M}(t)$. However, all process model matrices must be known precisely. A comparison with the parity equation approach shows similarities.

2.4. Fault-detection with parity equations

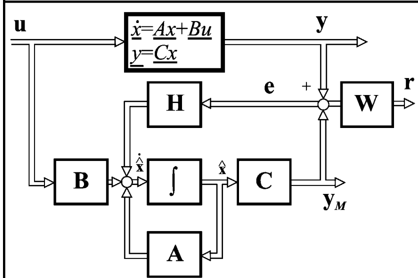
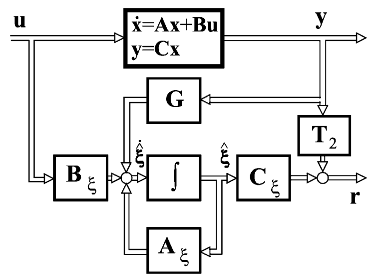
A straightforward model-based method of fault-detection is to take a fixed model G_M and run it parallel to the process, thereby forming an output error, see Table 5.

$$r'(s) = [G_\mathrm{p}(s) - G_\mathrm{M}(s)]u(s) \quad (1)$$

If $G_\mathrm{p}(s) = G_\mathrm{M}(s)$, the output error then becomes for additive input and output faults, Table 2.

$$r'(s) = G_\mathrm{p}(s)\, f_\mathrm{u}(s) + f_\mathrm{y}(s) \quad (2)$$

Table 4
Fault-detection with observers for dynamic processes

<table>
<tr><td>State observer</td><td>Output observer</td></tr>
<tr><td colspan="2">Process model:
$\dot{\mathbf{x}}(t) = \mathbf{A}\,\mathbf{x}(t) + \mathbf{B}\,\mathbf{u}(t) + \mathbf{F}\,\mathbf{v}(t) + \mathbf{L}\,\mathbf{f}_L(t)$
$\mathbf{y}(t) = \mathbf{C}\,\mathbf{x}(t) + \mathbf{N}\,\mathbf{n}(t) + \mathbf{M}\,\mathbf{f}_M(t)$
$\mathbf{v}(t)$, $\mathbf{n}(t)$: disturbance signals; $\mathbf{f}_L$, $\mathbf{f}_M$: additive fault signals</td></tr>
<tr><td>
</td><td>
</td></tr>
<tr><td>Observer equations:
$\dot{\hat{\mathbf{x}}}(t) = \mathbf{A}\,\hat{\mathbf{x}}(t) + \mathbf{B}\,\mathbf{u}(t) + \mathbf{H}\,\mathbf{e}(t)$
$\mathbf{e}(t) = \mathbf{y}(t) - \mathbf{C}\,\hat{\mathbf{x}}(t)$</td><td>$\dot{\hat{\boldsymbol{\xi}}}(t) = \mathbf{A}_\xi\,\hat{\boldsymbol{\xi}}(t) + \mathbf{B}_\xi\,\mathbf{u}(t) + \mathbf{H}_\xi\,\mathbf{y}(t)$
$\boldsymbol{\eta}(t) = \mathbf{C}_\xi\,\hat{\boldsymbol{\xi}}(t)$
$\xi(t) = \mathbf{T}_1\,\mathbf{x}(t)$: transformation</td></tr>
<tr><td>Residuals:
• $\Delta\mathbf{x}(t) = \mathbf{x}(t) - \mathbf{x}_0(t)$
• $\mathbf{e}(t)$
• $\mathbf{r}(t) = \mathbf{W}\,\mathbf{e}(t)$
Special observers:
- fault-sensitive filters
(**H** such, that $\mathbf{r}(t)$ defin. direct.)
- dedicated observers
(for different sensor outputs)</td><td>$\mathbf{r}(t) = \mathbf{C}_\xi\,\boldsymbol{\xi}(t) - \mathbf{T}_2\,\mathbf{y}(t)$
- independent of $\mathbf{x}(t)$, $\mathbf{u}(t)$, $\mathbf{v}(t)$
- dependent on $\mathbf{f}_L(t)$, $\mathbf{f}_M(t)$
Design equations:
$\mathbf{T}_1\,\mathbf{A} - \mathbf{A}_\xi\mathbf{T}_1 = \mathbf{H}_\xi\,\mathbf{C}$
$\mathbf{B}_\xi = \mathbf{H}_1\,\mathbf{B}$
$\mathbf{T}_1\,\mathbf{V} = \mathbf{0}$
$\mathbf{C}_\xi\mathbf{T}_1 - \mathbf{T}_2\,\mathbf{C} = \mathbf{0}$</td></tr>
</table>

Another possibility is to generate an equation error (polynominal error) or an input error as in Table 6 (Gertler, 1998).

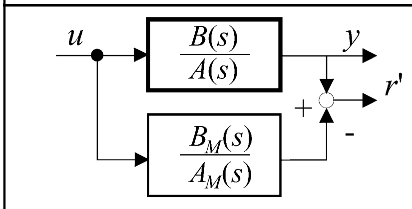
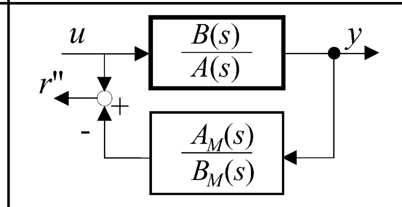
The residuals depend in all cases only on the additive input faults $f_u(t)$ and output faults $f_y(t)$. The same procedure can be applied for multivariable processes by using a state space model, see Table 6.

The derivatives of the signals can be obtained by state variable filters (Höfling, 1996). Corresponding equations exist for discrete-time and are easier to implement for the state space model. The residuals shown in Tables 5 and 6 left are direct residuals. If the parity equations are formulated for more than one input and one output, it becomes possible to generate structured residuals such that faults do not influence all residuals. This improves the isolability of faults (Gertler, 1998). For example, the components of matrix **W** for the state space model, Table 6 right, are selected such that, e.g., one measured variable has no impact on a specific residual. Parity equations are suitable for the detection and isolation of additive faults. They are simpler to design and to implement than output observer-based approaches and may be made to lead to the same results.

2.5. Fault-detection with signal models

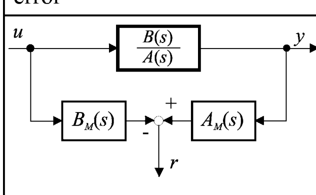
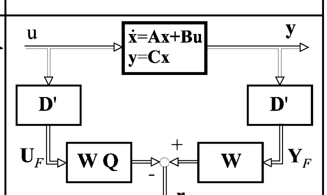
Many measured signals $y(t)$ show oscillations that are of either harmonic or stochastic nature, or both. If changes in these signals are related to faults in the process, actuator or sensor, a signal analysis is a further source of information. Especially for machine vibration, sensors for position, speed or acceleration are used to detect, for example, imbalance and bearing faults (turbo machines), knocking (Diesel engines) or chattering (metal-grinding machines) (Kolerus, 2000). But also signals from many other sensors, like electrical current, position, speed, force, flow and pressure, may show oscillations with a variety of higher frequencies than the usual process dynamic responses. The extraction of

Table 5
Fault-detection with different forms of parity equations for linear input/output models

Output error	Input error
	
Parity equations: $r'(s) = y(s) - \frac{B_M(s)}{A_M(s)} u(s)$ $r'(t) = \psi_r'^T(t)\Theta_{Mr} + \psi_a^T(t)\Theta_{Ma} - \psi_b'^T(t)\Theta_{Mb}$	$r''(s) = u(s) - \left(\frac{A_M(s)}{B_M(s)}\right) y(s)$ $r''(t) = \psi_b''^T(t)\Theta''_{Mb} - \psi_a^T(t)\Theta_{Ma}$
$B_M(s)=b_0+b_1s+...+b_ms^m$ $A_M(s)=1+a_1s+...+a_ns^n$ $\Theta_{Mr}^T=[\ 1\ a_1 a_2 ... a_n\ ]$ $\psi_b^T=[\ u\ u^{(1)} u^{(2)} ... u^{(m)}\ ]$ $\psi_a^T=[\ y\ y^{(1)} y^{(2)} ... y^{(n)}\ ]$	$\Theta''^T_{Mb} = \frac{1}{b_0}[\ 1\ b_1 b_2 ... b_m\ ]$ $\psi_b^T=[u\ u^{(1)} u^{(2)} ... u^{(m)}]$

fault-relevant signal characteristics can in many cases be restricted to the amplitudes $y_0(\omega)$ or amplitude densities $|y(i\omega)|$ within a certain bandwidth $\omega_{\min} \leq \omega \leq \omega_{\max}$ of the signal by using of bandpass filters. Also parametric signal models can be used, which allow the main frequencies and their amplitudes to be directly estimated, and which are especially sensitive to small frequency changes. This is possible by modeling the signals as a superposition of damped sinusoids in the form of discrete-time ARMA (autoregressive moving average) models (Burg, 1968; Neumann, 1991).

Table 6
Fault-detection with parity equations for dynamic processes

Input/output model, equation error	State space model
	
Parity equations: $r(s) = A_M(s)y(s) - B_M(s)u(s)$ $r(t) = \psi_a^T(t)\Theta_{Ma} - \psi_b^T(t)\Theta_{Mb}$	$\mathbf{Y}_F(t)=\mathbf{T}\,\mathbf{X}(t)+\mathbf{Q}\,\mathbf{U}_F(t)$ $\mathbf{W}\,\mathbf{Y}_F(t)=\mathbf{W}\,\mathbf{T}\,\mathbf{x}(t)+\mathbf{W}\,\mathbf{Q}\,\mathbf{U}_F(t)$ $\mathbf{W}\,\mathbf{T}=0$ $\mathbf{r}(t)=\mathbf{W}(\mathbf{Y}_F(t)-\mathbf{Q}\,\mathbf{U}_F(t))$
$B_M(s)=b_0+b_1s+...+b_ms^m$ $A_M(s)=1+a_1s+...+a_ns^n$ $\Theta_{Mb}^T=[\ b_0 b_1 ... b_m]$ $\Theta_{Ma}^T=[\ 1\ a_1 a_2 ... a_n]$ $\psi_b^T=[\ u\ u^{(1)} u^{(2)} ... u^{(m)}]$ $\psi_a^T=[\ y y^{(1)} ... y^{(n)}]$	$\mathbf{D'u} = [\ u u^{(1)} ... u^{(m)}\ ]^T = \mathbf{U}_F$ $\mathbf{D'y} = [\ \mathbf{y}\mathbf{y}^{(1)} ... \mathbf{y}^{(n)}\ ]^T = \mathbf{Y}_F$ $\mathbf{T} = [\ C\ CA\ CA^2 ...\ ]^T$ $\mathbf{Q} = \begin{bmatrix} 0 & 0 & 0 \ldots \\ CB & 0 & 0 \\ CAB & CB & 0 \\ \mathrm{M} & & \end{bmatrix}$

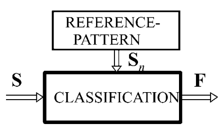
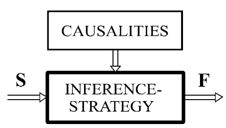
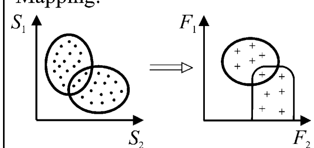
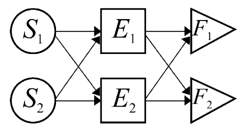
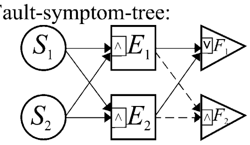
3. Fault diagnosis methods

The task of fault diagnosis consists of the determination of the type of fault with as many details as possible such as the fault size, location and time of detection. The diagnostic procedure is based on the observed analytical and heuristic symptoms and the heuristic knowledge of the process. The inputs to a knowledge-based fault diagnosis system are all available symptoms as facts and the fault-relevant knowledge about the process, mostly in heuristic form. The symptoms may be presented just as binary values [0,1] or as, e.g., fuzzy sets to take gradual sizes into account.

3.1. Classification methods

If no further knowledge is available for the relations between features and faults classification or pattern recognition methods can be used, Table 7. Here, reference vectors $\mathbf{S}_n$ are determined for the normal behavior. Then the corresponding input vectors $\mathbf{S}$ of the symptoms are

Table 7
Methods of fault diagnosis

Classification methods	Inference methods
	
Without a-priori knowledge on symptom-causalities. Mapping:  $\mathbf{S}^T = [S_1, S_2 \ldots S_n]$ $\mathbf{F}^T = [F_1, F_2 \ldots F_m]$	With a-priori knowledge on symptom-causalities. Causal network:  Fault-symptom-tree: 
Classification: - statistical - geometrical - neural nets - fuzzy clusters	Rules: If $< S_1 \wedge S_2 >$ Then $< E_1 >$ Diagnostic reasoning: - Boolean logic: facts binary - Approximative reasoning: - Probabilistic facts: probability densities - Fuzzy facts: fuzzy sets

determined experimentally for certain faults $\mathbf{F}_j$. The relationship between **F** and **S** is therefore learned (or trained) experimentally and stored, forming an *explicit knowledge base*. By comparison of the observed **S** with the normal reference $\mathbf{S}_n$, faults **F** can be concluded.

One distinguishes between *statistical* or *geometrical classification methods*, with or without certain probability functions (Tou & Gonzalez, 1974). A further possibility is the use of neural networks because of their ability to approximate non-linear relations and to determine flexible decision regions for **F** in continuous or discrete form (Leonhardt, 1996). By fuzzy clustering the use of fuzzy separation areas is possible.

3.2. Inference methods

For some technical processes, the basic relationships between faults and symptoms are at least partially known. Then this a priori knowledge can be represented in causal relations: fault → events → symptoms. Table 7 shows a simple causal network, with the nodes as states and edges as relations. The establishment of these causalities follows the fault-tree analysis (FTA), proceeding from faults through intermediate events to symptoms (the physical causalities) or the event-tree analysis (ETA), proceeding from the symptoms to the faults (the diagnostic forward-chaining causalities). To perform a diagnosis, this qualitative knowledge can now be expressed in form of rules: IF <condition> THEN <conclusion>. The condition part (premise) contains facts in the form of symptoms S_i as inputs, and the conclusion part includes events E_k and faults F_j as a logical cause of the facts. If several symptoms indicate an event or fault, the facts are associated by AND and OR connectives, leading to rules in the form

- IF $< S_1$ AND $S_2 >$ THEN $<E_1>$
- IF $< E_1$ OR $E_2 >$ THEN $<F_1>$.

For the establishment of this heuristic knowledge several approaches exist, see (Torasso & Console, 1974). In the classical fault-tree analysis the symptoms and events are considered as binary variables, and the condition part of the rules can be calculated by Boolean equations for parallel-serial-connection, see, e.g. (Barlow & Proschan, 1975; Freyermuth, 1993). However, this procedure has not proved to be successful because of the continuous nature of faults and symptoms. For the diagnosis of technical processes approximate reasoning is more appropriate. A recent survey on learning methods for rule-based diagnosis is given in (Füssel & Isermann, 2000).

The summary of some basic fault-detection and diagnosis methods presented in Sections 2 and 3 was limited to linear processes mainly. Some of the methods can also be directly applied for *non-linear processes*, as e.g., signal analysis, parity equations and parameter estimation. However, all the methods have to be adapted to the real processes. In this sense the basic methods should be considered as "tools", which have to be combined properly in order to meet the practical requirements for real faults of real processes.

4. Applications of model- and signal-based fault diagnosis

In the following some results from case studies and in-depth investigations of model-based fault-detection methods are briefly described. The examples are selected such that they show different approaches and process adapted solutions which can be transferred to other similar technical processes.

4.1. Fault diagnosis of a cabin pressure outflow valve actuator of a passenger aircraft

The air pressure control in passenger aircraft is manipulated by DC motor driven outflow valves. The design of the outflow valve is made fault tolerant by two brushless DC motors which operate over the gear to a lever mechanism moving the flap, Fig. 5. The two DC motors form a duplex system with dynamic redundancy and cold standby, Fig. 6. Therefore, a fault-detection for both DC motors is required to switch from the possibly faulty one to the standby motor.

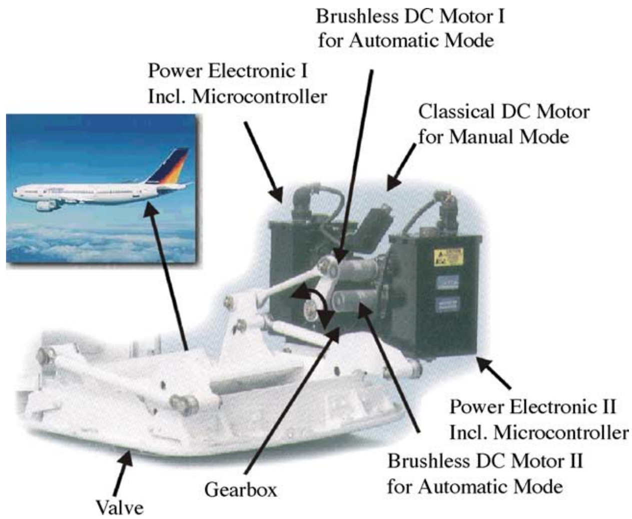


Fig. 5. Actuator servo-drive for cabin pressure control (Nord Micro).

In the following it is shown how the fault-detection was realized by combining parameter estimation and parity equations with implementation on a low cost microcontroller (Moseler & Isermann, 2000a; Moseler, Heller, & Isermann, 1999; Moseler & Müller, 2000).

A detailed model of the brushless DC motor for all three phases is given in (Isermann, 2003a; Moseler et al., 1999). It could be shown that for the case of fault-detection averaged values (by low pass filter) of the voltage $U(t)$ and the current $I(t)$ to the stator coils can be assumed. This leads to the voltage equation of the electrical subsystem.

$$U(t) - k_E\omega_r(t) = RI(t) \tag{3}$$

with R the overall resistance and k_E the magnetic flux linkage. The generated rotor torque is proportional to the effective magnetic flux linkage $k_T < k_E$

$$T_r(t) - k_T I(t) \tag{4}$$

(In ideal cases $k_E = k_T$). The mechanical part is then described by

$$J_r\dot{\omega}_r(t) = k_T I(t) - T_f(t) - T_L(t) \tag{5}$$

with the moment of inertia J_r, and the Coulomb friction torque

$$T_f(t) = c_f \operatorname{sign} \omega_r(t) \tag{6}$$

and the load torque $T_L(t)$. The gear ratio ν relates the motor shaft position ϕ_r to the flap position ϕ_g

$$\varphi_g = \frac{\varphi_r}{\nu} \tag{7}$$

with $\nu = 2500$. The load torque of the flap is a non-linear function of the position ϕ_g

$$T_L = c_s f(\varphi_g)$$

and is approximately known around the steady-state operation point. (For the experiments the flap was replaced by a lever with a spring). For fault-detection following measurements are available: $U(t)$, $I(t)$, $\phi_r(t)$, $\phi_g(t)$. Using the notation

$$y(t) = \boldsymbol{\psi}^T(t)\boldsymbol{\theta} \tag{8}$$

two equations were used for *parameter estimation*

- electrical subsystem

$$y(t) = U(t), \qquad \boldsymbol{\psi}^T(t) = [I(t)\omega_r(t)]; \qquad \boldsymbol{\theta}^T = [Rk_E] \tag{9}$$

- mechanical subsystem

$$y(t) = k_T I(t) - c_s f(\varphi_g(t) - J_r\dot{\omega}_r(t)) \qquad \boldsymbol{\psi}^T(t) = [\operatorname{sign} \omega_r t]; \qquad \boldsymbol{\theta}^T = [c_f](J_r \text{ known}) \tag{10}$$

Hence, three parameters $\widehat{R}, \widehat{k}_E$, and $\widehat{c}_f$ are estimated. Various parameter estimation methods were applied like: recursive least squares (RLS), discrete square root filtering (DSFI), fast DSFI (FSDFI), normalized least mean squares (NLMS) and compared. The *parity equations* are obtained from the basic two Eqs. (3) and (5) by assuming known parameters (obtained from parameter estimation)

$$r_1(t) = U(t) - RI(t) - k_E\omega_r(t) \tag{11}$$

$$r_2(t) = k_T I(t) - J_r\dot{\omega}_r(t) - c_f \operatorname{sign} \omega_r(t) - c_s f(\varphi_g) \tag{12}$$

$$r_3(t) = U(t) - \frac{R}{k_T}(J_r\dot{\omega}_r(t) + c_s f(\varphi_g) + c_f \operatorname{sign} \omega_r(t) + k_E\omega_r(t) \tag{13}$$

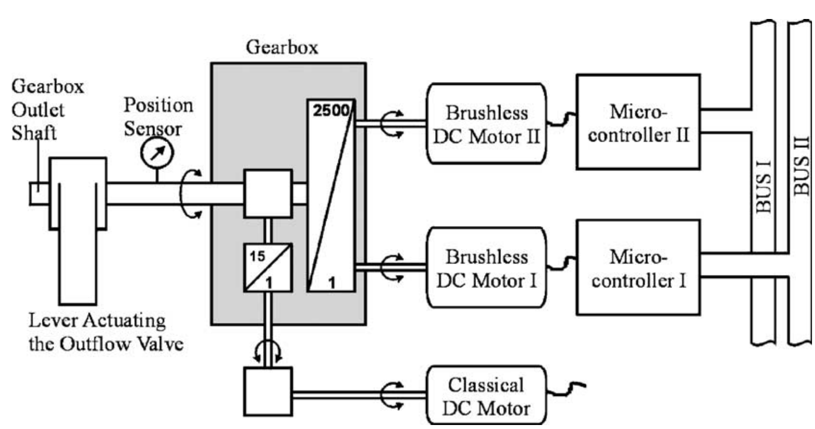


Fig. 6. Redundant DC motor drive system for the outflow valve.

$$r_4(t) = \varphi_g(t) - \frac{\varphi_r(t)}{v} \quad (14)$$

Each of the residuals is decoupled from one measured signal. r_1 is independent from ϕ_g, r_2 from U, r_3 from I, r_4 from all but ϕ_r. (ϕ_r is assumed to be correct. It can directly be supervised by a logic evaluation within the motor electronics). Fig. 7 shows measured signals, parameter estimates and residuals for five different implemented faults. The actuator was operating in closed loop with slow triangle changes of the reference variable (setpoint). The fault-detection methods, including differentiating filter (SVF) were implemented on a digital signal processor TI TMS 320 C40 with signal sampling period $T_0 = 1$ ms. The results for fault-detection are summarized in Table 8.

The sign and size of changes for the parameter estimates with FDSFI clearly allow to identify the parametric faults and for the parity residuals the respective additive (offset) sensor faults. But there are also cross couplings: for parametric faults some residuals show changes and for sensor additive faults some parameter estimates change (except for ϕ_g), which can all be interpreted by the equations used. According to (Gertler, 1998) the symptom pattern is weakly isolating as a parametric fault of R and an additive fault in U differ only in one symptom. However, all faults can be isolated. Including the standard deviation of the symptoms isolability can be improved (Moseler, 2001). By processing eight symptoms with a rule-based fuzzy-logic diagnosis system, finally 10 different faults could be diagnosed (Moseler and Müller, 2000b; Moseler, 2001).

If the input signal U stays approximately constant, only parity equations should be applied, which then may indicate faults. Then for isolating or diagnosing the faults a test signal on U can be applied for short time to gain deeper information. Hence, by applying both parameter estimation and parity equations a good fault coverage can be obtained. Because the position sensors of the rotor ϕ_r and the shaft ϕ_g yield redundant information, sensor fault-detection for ϕ_g was used to reconfigure the closed loop after failure of ϕ_g by using ϕ_r as control variable (Moseler, 2001). The described combined fault-detection methodology needs about 8 ms calculation time on a 16 bit microcontroller. Therefore, online implementation in a smart actuator is possible by only measuring four easy accessible variables U, I and ω_r and ϕ_g.

4.2. Supervision of the lateral driving behavior of passenger cars

Based on theoretical modeling of the lateral behavior of a passenger car, the characteristic velocity is considered as a parameter determining the kind of the steering behavior, like understeering or oversteering. This characteristic value is used as a "fault-detection feature" due to Fig. 1 to classify the behavior with regard to normal or critical driving behavior and such indicating also faulty behavior, like instability.

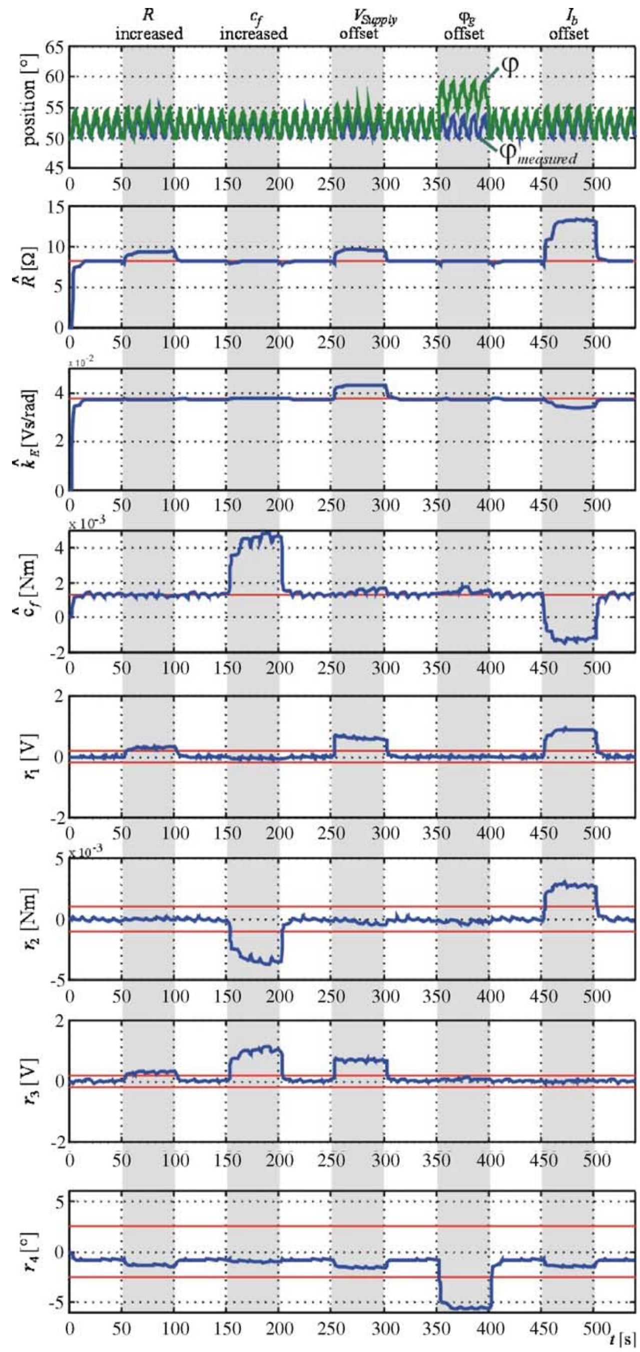


Fig. 7. Resulting symptoms from parameter estimation and parity equations by measuring $U(t)$, $I(t)$, $\omega(t)$,$\phi_g(t)$ and $\phi_r(t)$.

Table 8
Parameter deviations and parity equation residuals for different actuator faults (0 no significant change; + increase; ++ large increase; − decrease; −− large decrease)

Faults	Parameter estimates			Residuals of parity equations			
	$\hat{R}$	$\hat{k}_E$	$\hat{c}_f$	r_1	r_2	r_3	r_4
Incr. R	+	0	0	+	0	+	0
Incr. c_f	0	0	++	+	−−	++	0
Offset U	+	+	0	++	0	++	0
Offset ϕ_g	0	0	0	+	0	0	0
Offset I_b	++	−	−−	++	++	0	−−

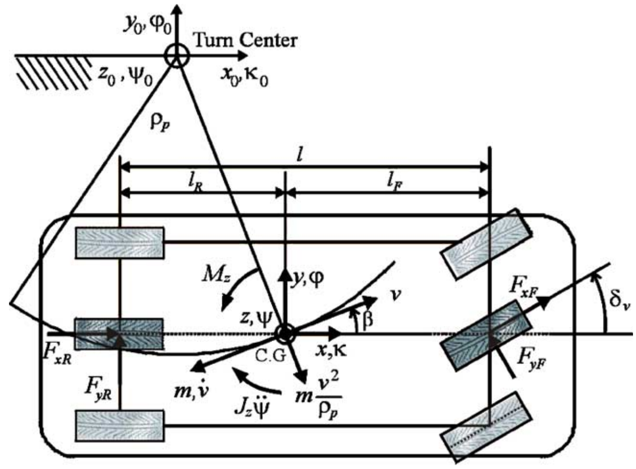


Fig. 8. Scheme for modeling the lateral vehicle behavior with a one-track model.

4.2.1. Vehicle model

For deriving the lateral dynamics, a coordinate system is fixed to the center of gravity (CG) and Newton's laws are applied, Fig. 8. Roll, pitch, bounce, and deceleration dynamics are neglected to reduce the model to two degrees of freedom: the lateral position and yaw angle states. The resulting non-linear dynamic model, known as the one-track model, is

$$\begin{bmatrix} \ddot{y} \\ \ddot{\psi} \end{bmatrix} = \begin{bmatrix} -\dfrac{c'_{\alpha F} + c_{\alpha R} + m\dot{v}}{mv} & \dfrac{c_{\alpha R} l_R - c'_{\alpha F} l_F}{mv} \\ \dfrac{c_{\alpha R} l_R - c'_{\alpha F} l_F}{J_z v} & -\dfrac{c_{\alpha R} l_R^2 + c'_{\alpha F} l_F^2}{J_z v} \end{bmatrix} \begin{bmatrix} \dot{y} \\ \dot{\psi} \end{bmatrix} + \begin{bmatrix} \dfrac{c'_{\alpha F}}{m i_{st}} \\ \dfrac{c'_{\alpha F} l_F}{J_s i_{st}} \end{bmatrix} \delta_{st} \tag{15}$$

see, e.g. (Isermann, 2001). The symbols are explained in Table 9. Although the one-track model is relatively simple, it has been proven to be a good approximation for vehicle dynamics when lateral acceleration is limited to 0.4 g on normal dry asphalt roads.

4.2.2. Stability of vehicles

Based on the state equation of the one-track model the characteristic equation det (s **I** -**A**) = 0 of the lateral vehicle dynamics becomes

$$s^2 + \frac{\overbrace{(J_z + m l_F^2) c'_{\alpha F} + (J_z + m l_R^2) c_{\alpha R}}^{a_1}}{J_z m v} s + \frac{\overbrace{c'_{\alpha F} c_{\alpha R} (l_F + l_R)^2 + m v^2 (c_{\alpha R} l_R - c'_{\alpha F} l_F)}^{a_0}}{J_z m v^2} = 0 \tag{16}$$

According to the Hurwitz stability criterion, stability requires that $a_1 > 0$ and $a_0 > 0$. As $a_1 > 0$ is always satisfied, because no negative values arise, only a_0 has to be considered. With the characteristic velocity

$$v_{ch}^2(t) = \frac{c'_{\alpha F}(t) c_{\alpha R}(t)^2}{m(c_{\alpha R}(t) l_R - c'_{\alpha F}(t) l_F)} \tag{17}$$

the following stability condition results:

$$\overbrace{c'_{\alpha F} c_{\alpha R} (l_F + l_R)^2 + m v^2 (c_{\alpha R} l_R - c'_{\alpha F} l_F}^{a_0} > 0 \Rightarrow 1 + \frac{v^2}{v_{ch}^2} > 0 \tag{18}$$

Table 9
Symbols for vehicle variables and parameters

Symbol	Description	Value	Unit
x	Longitudinal position error	–	[m]
y	Lateral position error	–	[m]
z	Vertical position error	–	[m]
ψ	Yaw angle	–	[rad]
δ	Steering angle	–	[rad]
δ_{st}	Steering wheel angle	–	[rad]
β	Side slip angle	–	[rad]
m	vehicle mass	1720	[kg]
J_z	Mom. of inertia, z-axis	2275	[kg m^2]
v	Longitudinal velocity	–	[m/s]
$c'_{\alpha F}$	Effective front wheel cornering stiffness	50000	[N/rad]
$c_{\alpha R}$	Rear wheel cornering stiffness	60000	[N/rad]
l_F,l_R	Length of front, rear axle from CG	1.3/1.43	[m]
l	Length between front and rear axle	2.73	[m]
i_{st}	Steering system gear ratio	13.5	[–]
ρ	Radius	–	[m]
F_{xr}	Longitudinal force acting on rear tire	–	[N]
F_{xF}	Longitudinal force acting on front tire	–	[N]
F_{yR}	Side force acting on rear tire	–	[N]
F_{yF}	Side force acting on front tire	–	[N]

4.2.3. Circular test drive

A stationary circular test drive is now assumed. The dynamic equation of motion leads to the algebraic relationship

$$\frac{\dot{\psi}(t)}{\delta_{st}(t)} = \frac{1}{i_{st} l} \frac{v(t)}{1 + (v(t)/v_{ch}(t))^2} \tag{19}$$

With the measured steering wheel angle δ_{st} as the input, the velocity $v(t)$ and the yaw rate $\dot{\psi}(t)$ as the output, the quadratic characteristic velocity $v_{ch}^2(t)$ follows from (19)

$$v_{ch}^2(t) = -\frac{v^2(t)}{1 - (\delta_{st}(t) v(t)/\dot{\psi}(t) i_{st} l)} \tag{20}$$

Introducing the steering wheel angle $\delta_{st,0}$(t) for neutral steering yields in (19) with $v \ll v_{ch}$

$$\frac{\delta_{st}}{\delta_{st,0}} = 1 + \frac{v^2}{v_{ch}^2} \tag{21}$$

This leads to the definition of neutral-, under- and over-steering:

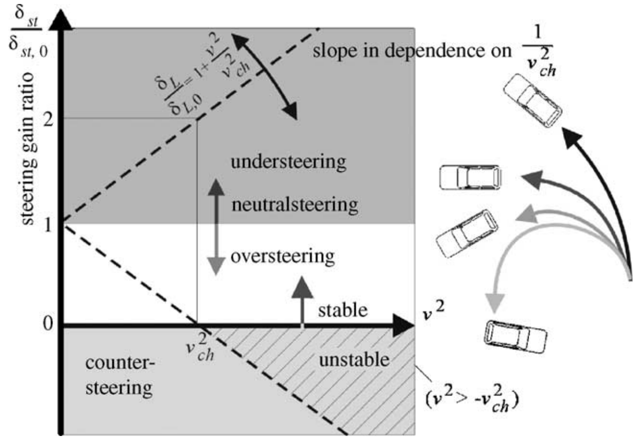


Fig. 9. Steering gain ratio in dependence on the speed v^2 and characteristic velocity v_{ch}^2.

- if $v_{\mathrm{ch}}^2 \to \mp\infty$ then neutralsteering behavior;
- if $v_{\mathrm{ch}}^2 > 0$ then understeering behavior;
- if $v_{\mathrm{ch}}^2 = 0$ then indifferent behavior;
- if $v_{\mathrm{ch}}^2 < 0$ then oversteering behavior.

Fig. 9 shows the different situations.

4.2.4. Characteristic velocity stability indicator CVSI

A driving situation detection is developed via the calculation of the characteristic velocity v_{ch} and a driving situation decision logic. The input of the model is the steering wheel angle signal δ_{st}. As output signal the yaw rate sensor $\dot{\psi}$ can be used to calculate the characteristic velocity v_{ch}, see (20). With help of the on-line calculated characteristic velocity v_{ch}, the over ground velocity v, and the steering wheel angle δ_{st} the current driving situation can be detected. For small steering angles $\delta_{\mathrm{st}} < \delta_{\mathrm{st,L}}$, it is assumed that the driving condition is mainly a straight run, just compensating for disturbances. If $\delta_{\mathrm{st}} \geq \delta_{\mathrm{st,L}}$ cornering can be assumed. Then a classification of different driving situations can be made as shown in Table 10 (Börner, Andréani, Albertos, & Isermann, 2002) with an indicator called characteristic velocity stability indicator (CVSI).

4.2.5. Experimental results

The following results are based on experimental data, which have been obtained using an Opel Omega vehicle on an airfield runway (Börner, 2004).

The test vehicle is equipped with special sensors for measuring the following signals: the steering wheel angle δ_{st}, lateral acceleration $\ddot{y}$, yaw rate $\dot{\psi}$, and ABS velocity $v_{1.4}$. The passenger cars velocity v has a large influence on the vehicles stability. Fig. 10 shows the behavior for a double lane change. After starting cornering, the vehicle shows first understeering, then neutral steering and oversteering behavior. At $t = 16.4$ and 17.8 s for a short time unstable behavior with counter steering can be observed. Further examples are shown in (Börner, 2004).

4.3. Combustion engines

Because of increased sensors, actuators and electronic functions the diagnosis of faults in combustion engines gets more complicated. However, model-based fault-detection offers new approaches by using the electronic control units not only for control but also for increased model-based fault diagnosis. Therefore an overall fault-diagnosis system for Diesel engines is briefly described. The inlet system, the injection and combustion as well as the exhaust system have been considered. The methods are based on an appropriate signal processing of measurable signals using signal- and process models to generate physically related features,

Table 10
Classification of different driving conditions (Λ: logical AND)

<table>
<tr><th colspan="3">Signal processing</th><th colspan="2">Driving condition</th><th>Stability</th><th>CVSI</th></tr>
<tr><td rowspan="2">$(\delta_{st} < \delta_{st,L}) \wedge (v^2 > 0)$</td><td colspan="2">$\dot{\psi} < \dot{\psi}_{thres}$</td><td rowspan="2">straight run</td><td>-</td><td>stable</td><td>-1</td></tr>
<tr><td colspan="2">$\dot{\psi} \geq \dot{\psi}_{thres}$</td><td>μ-split</td><td>unstable</td><td>0</td></tr>
<tr><td rowspan="6">$(\delta_{st} \geq \delta_{st,L}) \wedge (v^2 > 0)$</td><td rowspan="2">$v_{ch}^2 \geq 0$</td><td>-</td><td rowspan="6">cornering</td><td>understeering</td><td>stable</td><td>1</td></tr>
<tr><td>$v^2 \ll -v_{ch}^2$</td><td rowspan="2">neutralsteering</td><td rowspan="2">stable</td><td rowspan="2">2</td></tr>
<tr><td rowspan="4">$v_{ch}^2 < 0$</td><td>$v^2 \ll -v_{ch}^2$</td></tr>
<tr><td>$v^2 < -v_{ch}^2$</td><td>oversteering</td><td>stable</td><td>3</td></tr>
<tr><td>$v^2 = -v_{ch}^2$</td><td>high oversteering</td><td>indifferent</td><td>4</td></tr>
<tr><td>$v^2 > -v_{ch}^2$</td><td>breaking away</td><td>unstable</td><td>5</td></tr>
</table>

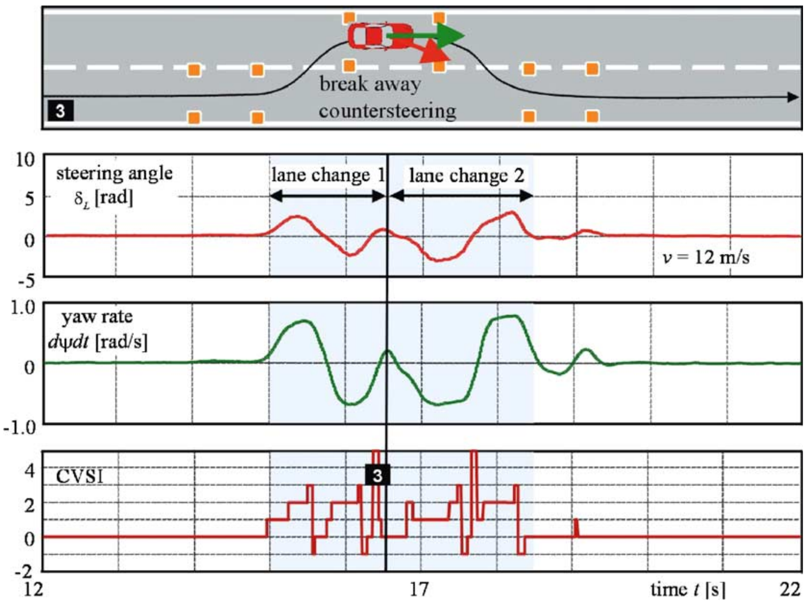


Fig. 10. Double lane change with speed v = 12 m/s: (a) steering angle; (b) yaw-rate; (c) CVSI: characteristic velocity indicator.

residuals and symptoms. Former publications on fault-detection of gasoline engines are, for example (Krishnaswami, Luth, & Rizzoni, 1995; Rizzoni & Samimy, 1996) or (Nielsen & Nyberg, 1993).

Fig. 11 shows the concept for the developed model-based fault-detection and diagnosis of the complete engine, see also (Kimmich, Schwarte, & Isermann, 2005; Schwarte, Kimmich, & Isermann, 2002). The engine is partitioned in three major subsystems: intake system, injection, combustion and crankshaft system as well the exhaust gas system. The actuators are commanded by the electronic control unit and act on different components of the combustion engine. In addition to the available mass production sensors only very few additional sensors are used. For each major subsystem, fault-detection methods are developed to detect faults in the shown components and to generate symptoms. Then the symptoms are processed with diagnosis methods to decide on faults according to their type and location. The investigated engine is an Opel 2 liter, 4 cylinder, 16 valve turbo charge DI Diesel engine with a power of 74 kW and a

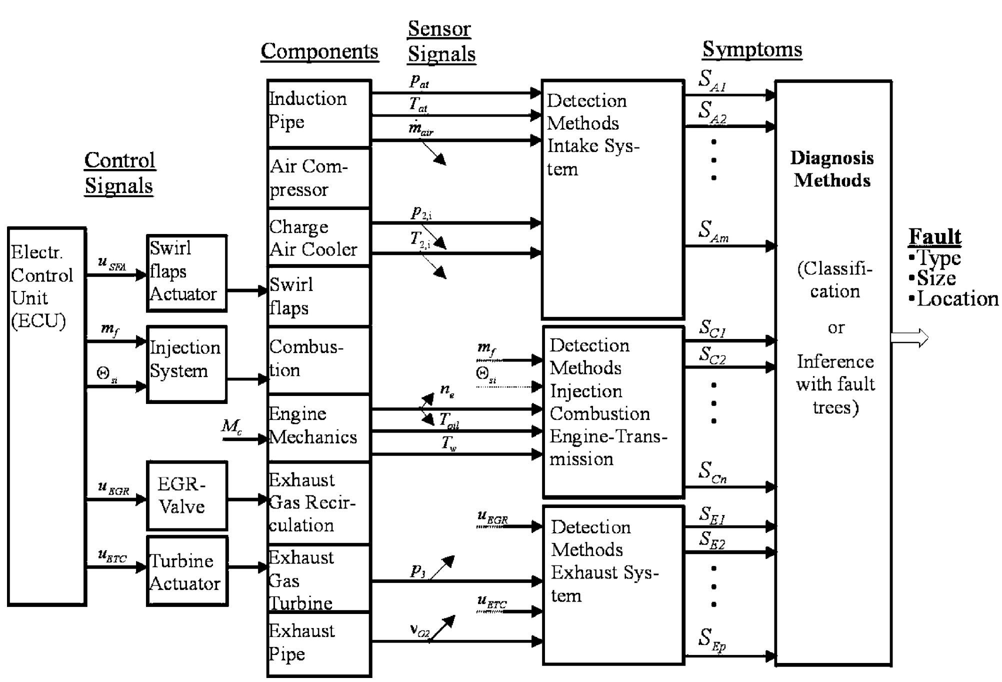


Fig. 11. Concept of a modular model-based fault-detection system of the complete combustion engine. Module 1: intake system; module 2: injection, combustion; module 3: exhaust system.

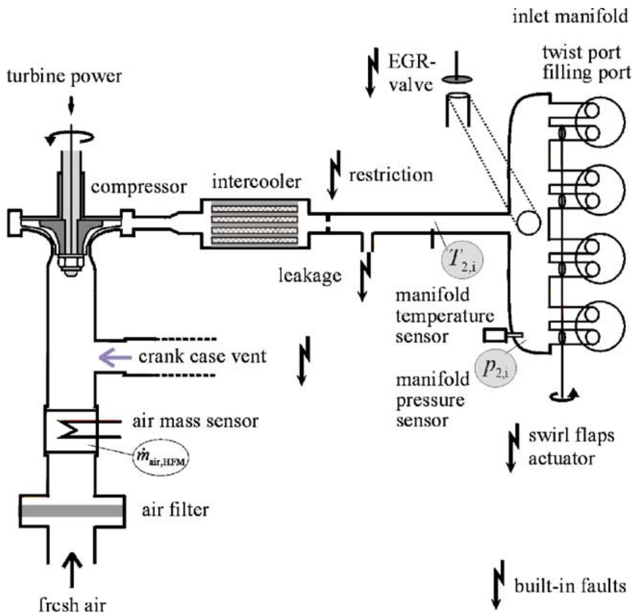


Fig. 12. Air path of the intake system with sensors and considered faults.

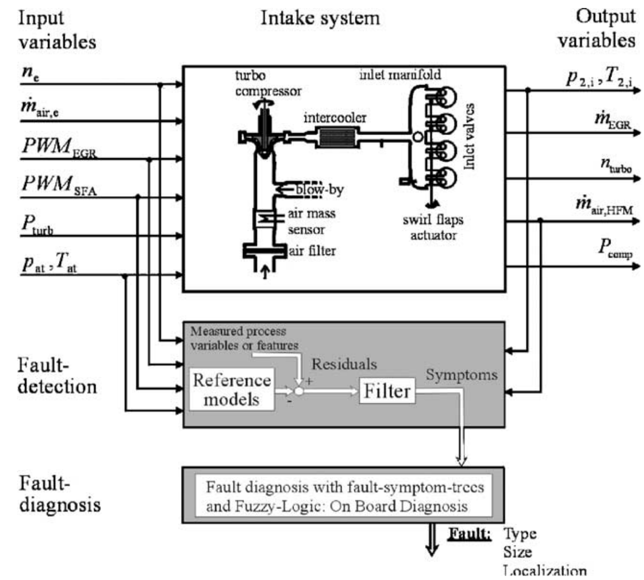


Fig. 13. Fault diagnosis structure of the intake system.

torque of 205 Nm. The engine employs exhaust gas recirculation and a variable swirl of the inlet gas for emission reduction.

Only the intake system can be considered here as example. As shown in Fig. 12 the air flows through the air filter, air mass flow sensor, compressor, intercooler and inlet manifold.

Measured input variables are the engine speed, the pulse width modulated signals for the EGR and SFA (swirl flaps) as well as the atmospheric pressure and temperature, see Fig. 13.

Measured output variables are manifold pressure, the manifold temperature and the air mass flow. The engine pumping, describing the air mass flow into the engine, was modeled with a semi-physical neural network model (LOLIMOT). It is a mean value model of one working cycle neglecting the periodic working principle. For the fault free description of the intake system 5 static reference

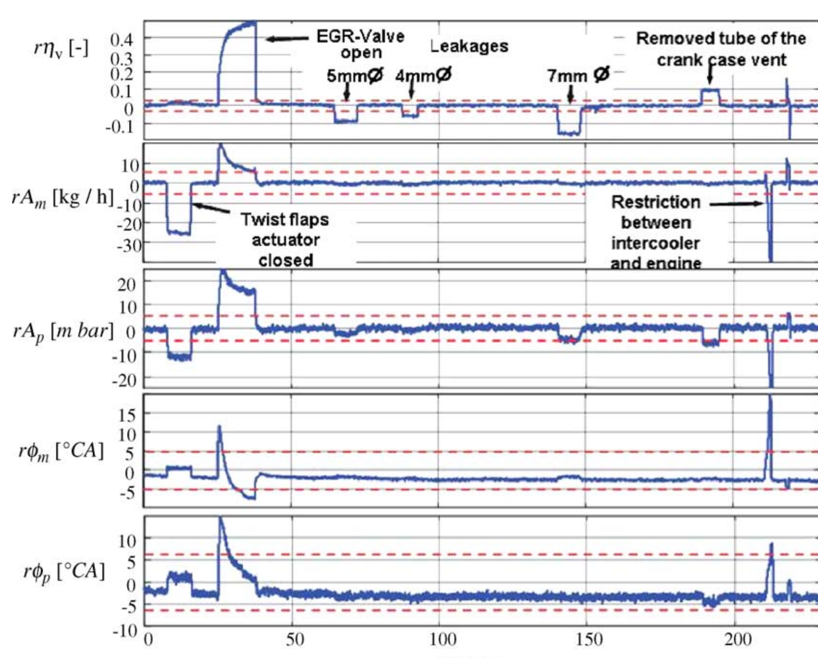


Fig. 14. Residual deflection in dependency on faults (online); 2000 min^{-1}, 130 Nm, $p_{2,i}$ = 1.5 bar, air flow 165 kg/h.

models were identified, which describe the volumetric efficiency, the amplitude of air mass flow oscillation, the phase of air mass flow oscillation, the amplitude of boost pressure oscillation depending on engine speed and manifold pressure. The reference models were identified for a closed EGR valve and opened swirl flaps actuator with a quasi stationary identification cycle. The identified non-linear reference models calculating special features are used to set up five independent parity equations yielding five residuals. The results of real-time fault-detection are presented in Fig. 14 for an exemplary operating point. Several faults were temporarily built into the intake system. The fault-detection thresholds are marked by dotted lines. The reference models for the volumetric efficiency, amplitude air mass flow oscillation, amplitude boost pressure oscillation, show the expected behavior in order to isolate the different faults. Similar methods were developed for the other parts of the Diesel engine, (Isermann, Schwarte, & Kimmich, 2004).

5. Conclusion

After a short introduction into model-based fault-detection methods, like parameter estimation, observers and parity equations, and fault-diagnosis methods, like classification and inference methods, three application examples were shown. For a *DC motor actuator* of an aircraft cabin pressure control the combination of parameter estimation and parity equations allows the detection of several parametric and additive faults by using four measurements, followed by the fault diagnosis with fuzzy-logic inferencing. Based on a dynamic one-track model of a *passenger car* a time-varying parameter, the characteristic velocity, can be calculated by measurement of three drive dynamic variables. A classification scheme then indicates different lateral driving conditions, from stable understeering to unstable countersteering. For fault diagnosis of *Diesel engines* three detection modules are proposed to generate symptoms based on mainly production-type sensors. The symptoms are generated with non-linear output error and input error parity equations for special model-based characteristic quantities like volumetric efficiency, oscillations of pressure, flow and (not shown here) for angular speed and oxygen content. The generation of about 20 symptoms then allow an in-depth fault diagnosis, e.g., by a fuzzy logic inference scheme.

The shown examples are only a small sample of many other developed and experimentally tested fault-detection and fault-diagnosis procedures, like for pneumatic and hydraulic actuators, robots and machine tools, AC motors with centrifugal and oscillating pumps, SI engines and automotive brake and active suspension systems. In all cases the model-based fault-detection and diagnosis has demonstrated a big step forward compared to limit and trend checking of some directly measurable variables. However, the methods have to be adapted to the physical properties of the processes and their sensor signals and some effort is needed to obtain the mostly non-linear dynamic models. In many cases the combination of parameter estimation and parity equations, the last one for directly measured and calculated characteristic quantities, has proven to result in a good fault diagnosis coverage and to be most efficient.

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