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, outflow valve, hydraulic actuator, lateral driving behaviour, 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:

(i) Early detection of small faults with abrupt or incipient time behaviour;

(ii) Diagnosis of faults in the actuator, process components or sensors;
(iii) Detection of faults in closed loops;
(iv) 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 behaviour.

2. MODEL-BASED FAULT-DETECTION METHODS

Different approaches for fault detection using mathematical models have been developed in the last 20 years, see, e.g., (Willsky, 1976; Himmelblau, 1978; Isermann, 1984, 1993, 1994; Gertler, 1998; Frank, 1990; Chen and Patton, 1999; Patton *et al.* 2000). 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. Figure 1 shows the basic structure of model-based fault detection. Based on measured input signals **U** and output signals **Y**, the detection methods generate residuals **r**, parameter estimates $\hat{\mathbf{\Theta}}$ or state estimates $\hat{x}$, which are called features. By comparison with the normal features, changes of features are detected, leading to analytical symptoms **s**.

For the application of model-based fault detection methods, the process configurations according to Figure 2 have to be distinguished. With regard to the inherent

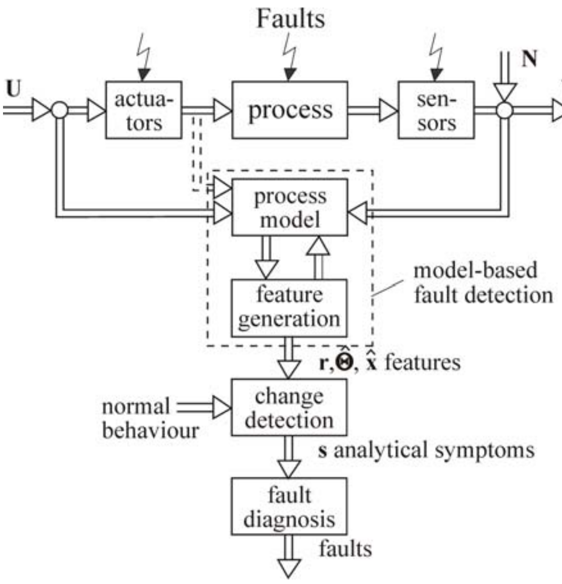


Fig. 1. General scheme of process model-based fault detection and diagnosis

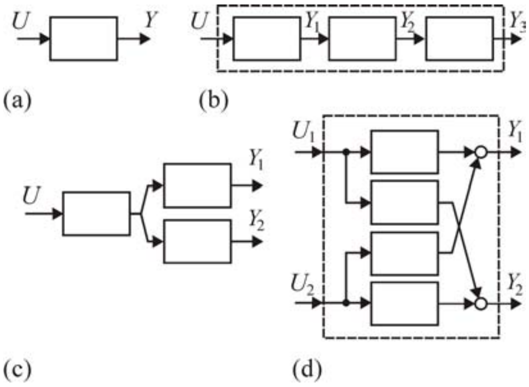


Fig. 2. Process configuration for model-based fault detection: (a) SISO (single-input single-output); (b) SISO with intermediate measurements; (c) SIMO (single-input multi-output); (d) MIMO (multi-input multi-output)

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 modelling

A fault is defined as an unpermitted deviation of at least one characteristic property of a variable from an acceptable behaviour. 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 Figure 3, abrupt fault (stepwise), incipient fault (drift-like), intermittent fault. With regard to the process models, the faults can be further classified. According to Figure 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 behaviour* (steady states) is frequently be 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

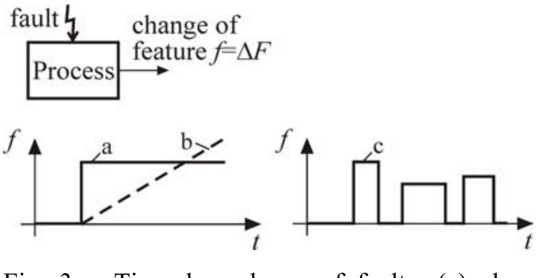


Fig. 3 Time-dependency of faults: (a) abrupt; (b) incipient; (c) intermittent

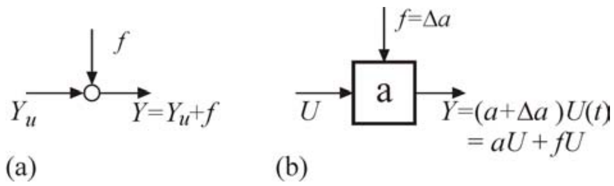
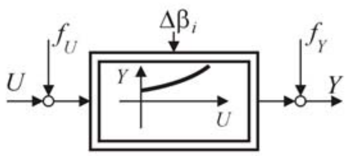


Fig. 4 Basic models of faults: (a) additive faults; (b) multiplicative faults

least squares, based on measurements of different input-output pairs $[Y_j, U_j]$. This method is applicable, e.g., or valves, pumps, drives, engines.

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


Measured signals: $U(t)$, $Y(t)$
Basic equation:
$Y=\beta_0+\beta_1 U+\beta_2 U^2+...+\beta_q U^q \rightarrow Y=\boldsymbol{\psi}_S^T \boldsymbol{\Theta}_S$
$\boldsymbol{\Theta}_S^T=[\beta_0 \beta_1 \ldots \beta_q]$ $\quad \boldsymbol{\psi}_S^T=[1\ U\ U^2 \ldots U^q]$
Additive faults: f_U input fault; f_Y output fault
Multiplicative faults: $\Delta\beta_i$ parameter faults

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.

2.2 Fault detection with parameter estimation

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 minimisation 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 optimisation methods and therefore iterative procedures, but may be more precise under the influence of process disturbances. The symptoms are deviations of the process parameters $\Delta\boldsymbol{\Theta}$. As the process parameters $\boldsymbol{\Theta}=f(\mathbf{p})$ depend on physically defined process coefficients $\mathbf{p}$ (like stiffness, damping filters, resistance), determination of changes $\Delta\mathbf{p}$ allows usually a deeper insight and makes fault diagnosis easier (Isermann 1992). Parameter estimation methods usually need a process input excitation and are especially suitable for the detection of multiplicative faults.

Table 2 Linear dynamic process models and fault modelling

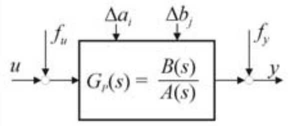
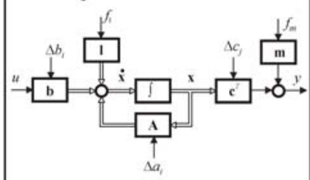
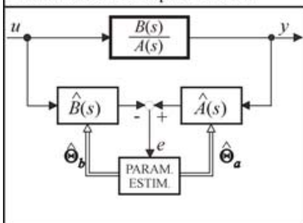
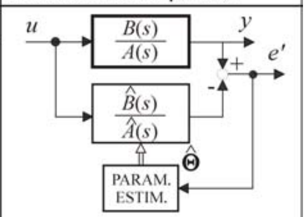
Input/output model	State space model
 Measured signals: $y(t)=Y(t)-Y_{00}$; $u(t)=U(t)-U_{00}$	
Basic equations: $y(t)=a_1 y^{(1)}(t)+...+a_n y^{(n)}(t)$ $=b_0 u(t)+b_1 u^{(1)}(t)+...+b_m u^{(m)}(t)$	$\dot{\mathbf{x}}(t)=\mathbf{A}\,\mathbf{x}(t)+\mathbf{b}u(t)$ $y(t)=\mathbf{c}^T\,\mathbf{x}(t)$
$y(t)=\boldsymbol{\psi}^T(t)\,\boldsymbol{\Theta}$ $\boldsymbol{\Theta}^T=[a_1 \ldots a_n\ b_0 \ldots b_m]$ $\mathbf{y}^T=[-y^{(1)}(t) \ldots -y^{(n)}(t)$ $u(t) \ldots u^{(m)}(t)]$	$\mathbf{A}=\begin{bmatrix} 0 & 0 & \cdot 1 \\ 0 & 1 & \cdot -a_1 \\ 1 & 0 & \cdot -a_2 \\ \vdots & \vdots & \end{bmatrix}$ $\mathbf{b}^T=[\ b_0\ \ b_1\ \ \ldots\ ]$ $\mathbf{c}^T=[\ 0\ \ 0\ \ \ldots\ 1\ ]$
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

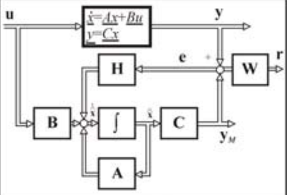
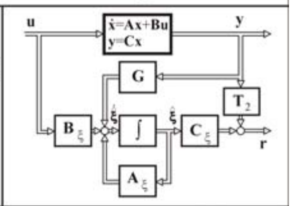
Table 3 Fault detection with parameter estimation methods for dynamic processes

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

2.3 Fault detection with observers

If the process parameters are known, either state observers or output observers can be applied, Table 4. Fault modelling is then performed with additive faults $\mathbf{f}_L$ at the input (additive actuator or process faults) and $\mathbf{f}_M$ at the output (sensor offset faults).

Table 4 Fault detection with observers for dynamic processes

State observer	Output observer
Process model: $\dot{\mathbf{x}}(t) = \mathbf{A}\,\mathbf{x}(t) + \mathbf{B}\,\mathbf{u}(t) + \mathbf{F}\,\mathbf{v}(t) + \mathbf{L}\,f_L(t)$ $\mathbf{y}(t) = \mathbf{C}\,\mathbf{x}(t) + \mathbf{N}\,\mathbf{n}(t) + \mathbf{M}\,f_M(t)$ $\mathbf{v}(t)$, $\mathbf{n}(t)$: disturbance signals; f_L, f_M: additive fault signals	
	
Observer equations: $\dot{\hat{\mathbf{x}}}(t) = \mathbf{A}\,\hat{\mathbf{x}}(t) + \mathbf{B}\,\mathbf{u}(t) + \mathbf{H}\,\mathbf{e}(t)$ $\mathbf{e}(t) = \mathbf{y}(t) - \mathbf{C}\,\hat{\mathbf{x}}(t)$	$\dot{\hat{\boldsymbol{\xi}}}(t) = \mathbf{A}_\xi\,\hat{\boldsymbol{\xi}}(t) + \mathbf{B}_\xi\,\mathbf{u}(t) + \mathbf{H}_\xi\,\mathbf{y}(t)$ $\boldsymbol{\eta}(t) = \mathbf{C}_\xi\,\hat{\boldsymbol{\xi}}(t)$ $\xi(t) = \mathbf{T}_1\,\mathbf{x}(t)$: transformation
Residuals: • $\Delta\mathbf{x}(t) = \mathbf{x}(t) - x_0(t)$ • $e(t)$ • $\mathbf{r}(t) = \mathbf{W}\,\mathbf{e}(t)$ Special observers: - fault-sensitive filters (**H** such, that $\mathbf{r}(t)$ defin. direct.) - dedicated observers (for different sensor outputs)	$\mathbf{r}(t) = \mathbf{C}_\xi\,\boldsymbol{\xi}(t) - \mathbf{T}_2\,\mathbf{y}(t)$ - independent on $\mathbf{x}(t)$, $\mathbf{u}(t)$, $\mathbf{v}(t)$ - dependent on $f_L(t)$, $f_M(t)$ Design equations: $\mathbf{T}_1\mathbf{A} - \mathbf{A}_\xi\mathbf{T}_1 = \mathbf{H}_\xi\,\mathbf{C}$ $\mathbf{B}_\xi = \mathbf{H}_1\,\mathbf{B}$ $\mathbf{T}_1\,\mathbf{V} = \mathbf{0}$ $\mathbf{C}_\xi\mathbf{T}_1 - \mathbf{T}_2\mathbf{C} = \mathbf{0}$

a) State observers
The classical state observer can be applied if the faults can be modelled 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:

Dedicated observers for multi-output processes
Observer, excited by one output: One observer is driven by one sensor output. The other outputs **y** are reconstructed and compared with measured outputs **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 **y** are compared with the measured outputs **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).

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

b) 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 $r(t)$ can be designed such that they are independent on the unknown inputs $\mathbf{v}(t)$, and of the state $\mathbf{x}(t)$ and $\mathbf{u}(t)$ by special determination of the matrices $\mathbf{C}_\xi$ and $\mathbf{T}_2$. The residuals then depend only on the additive faults $\mathbf{f}_L(t)$ and $\mathbf{f}_M(t)$. However, all process model matrices must be known precisely. A comparison with the parity equation approach shows similarities.

3.4 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

$$r'(s) = [G_p(s) - G_M(s)]u(s) \tag{1}$$

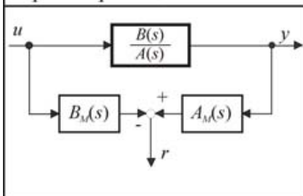
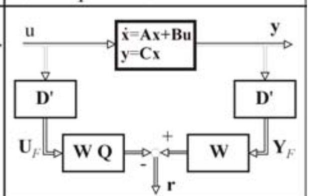
If $G_p(s) = G_M(s)$, the output error then becomes for additive input and output faults, Table 2

$$r(s) = G_p(s) f_u(s) + f_y(s) \tag{2}$$

Another possibility is to generate a polynominal error or equation error, as shown in Table 5.

The residuals then depend 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 5.

Table 5 Fault detection with parity equations for dynamic processes

Input/output model	State space model
	
Parity equations: $r(s) = A_M(s)y(s) - B_M(s)u(s)$ $r(t) = \boldsymbol{\psi}_a^T(t)\boldsymbol{\Theta}_{Ma} - \boldsymbol{\psi}_a^T(t)\boldsymbol{\Theta}_{Mb}$	$\mathbf{Y}_F(t) = \mathbf{T}\,\mathbf{X}(t) + \mathbf{Q}\,\mathbf{U}_F(t)$ $\mathbf{W}\,\mathbf{Y}_F(t) = \mathbf{W}\,\mathbf{T}\,\mathbf{x}(t) + \mathbf{W}\,\mathbf{Q}\,\mathbf{U}_F(t)$ $\mathbf{W}\,\mathbf{T} = 0$ $\mathbf{r}(t) = \mathbf{W}(\mathbf{Y}_F(t) - \mathbf{Q}\,\mathbf{U}_F(t))$
$B_M(s) = b_0 + b_1 s + \ldots + b_m s^m$ $A_M(s) = 1 + a_1 s + \ldots + a_n s^n$ $\boldsymbol{\Theta}_{Mb}^T = [\,b_0\, b_1 \ldots b_m\,]$ $\boldsymbol{\Theta}_{Ma}^T = [\,a_1\, a_2 \ldots a_n\,]$ $\boldsymbol{\psi}_b^T = [\,u^{(1)} u^{(2)} \ldots u^{(n)}\,]$ $\boldsymbol{\psi}_a^T = [\,y\, y^{(1)} \ldots y^{(m)}\,]$	$\mathbf{D'u} = [\,u\,u^{(1)} \ldots u^{(m)}\,]^T = \mathbf{U}_F$ $\mathbf{D'y} = [\,\mathbf{y}\,\mathbf{y}^{(1)} \ldots \mathbf{y}^{(n)}\,]^T = \mathbf{Y}_F$ $\mathbf{T} = [\,C\;CA\;CA^2 \ldots\,]^T$ $\mathbf{Q} = \begin{bmatrix} 0 & 0 & 0 \ldots \\ CB & 0 & 0 \\ CAB & CB & 0 \\ \mathrm{M} & & \end{bmatrix}$

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. The components of matrix $\mathbf{W}$ are selected such that one measured variable has no impact on a specific residual. This allows to generate structured residuals in order to obtain good isolating patterns for the residuals, Gertler (1998). Hence, parity equations are suitable for the detection of additive faults. They are simpler to design and to implement than output observer-based approaches and lead approximately 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, unbalance 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 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 modelling the signals as a superposition of damped sinusoids in the form of discrete-time ARMA (autoregressive moving average) models (Burg, 1968, Neumann, 1991).

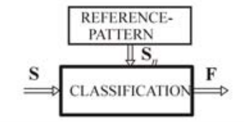
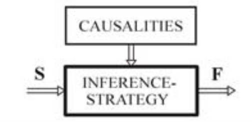
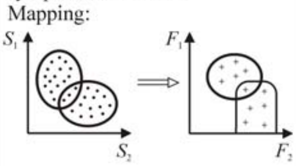
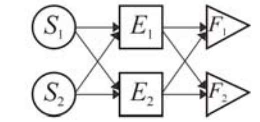
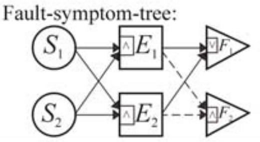
3. FAULT DIAGNOSIS METHODS

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, as shown in Figure 2. 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 6. Here, reference vectors $\mathbf{S}_n$ are determined for the normal behaviour. Then the corresponding input vectors $\mathbf{S}$ of the features are determined experimentally for certain faults F_j. The relationship between $\mathbf{F}$ und $\mathbf{S}$ is therefore learned (or trained) experimentally and stored, forming an *explicit knowledge base*. By comparison of the observed $\mathbf{S}$ with the normal reference $\mathbf{S}_n$, faults $\mathbf{F}$ can be concluded.

Table 6 Methods of fault diagnosis

<table>
<tr><th>Classification methods</th><th>Inference methods</th></tr>
<tr><td></td><td></td></tr>
<tr><td>Without a-priori knowledge on symptom-causalities.
Mapping:

$\mathbf{S}^T = [S_1, S_2 \dots S_n]$
$\mathbf{F}^T = [F_1, F_2 \dots F_m]$</td><td>With a-priori knowledge on symptom-causalities.
Causal network:

Fault-symptom-tree:
</td></tr>
<tr><td>Classification:
- statistical
- geometrical
- neural nets
- fuzzy clusters</td><td>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</td></tr>
</table>

One distinguishes between *statistical or geometrical classification methods*, with or without certain probability functions (Tou and 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 6 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 (Frost, 1986; Torasso and Console, 1989). 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 and 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 and learning methods for rule-based diagnosis gives Füssel (2000, 2003).

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, Figure 5. The two DC motors form a duplex system with dynamic redundancy and cold standby, Figure 6. Therefore, a fault detection for both DC motors is required to switch from the possibly faulty one to the standby motor.

In the following it is shown how the fault detection was realised by combining parameter estimation and parity equations with implementation on a low cost micro-controller, (Moseler and Isermann 2000; Moseler *et al.*

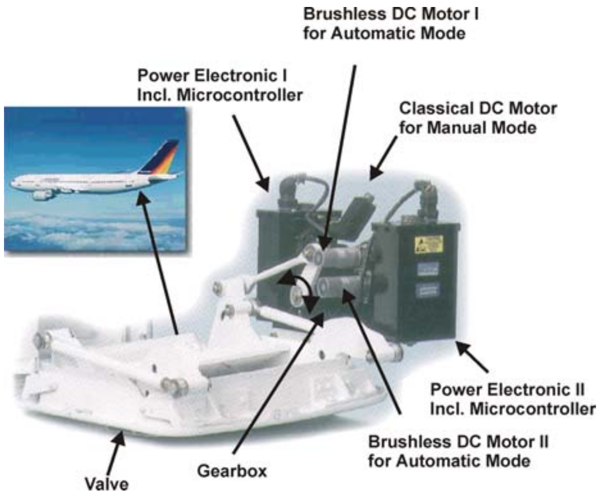


Fig. 5 Actuator servo-drive for cabin pressure control

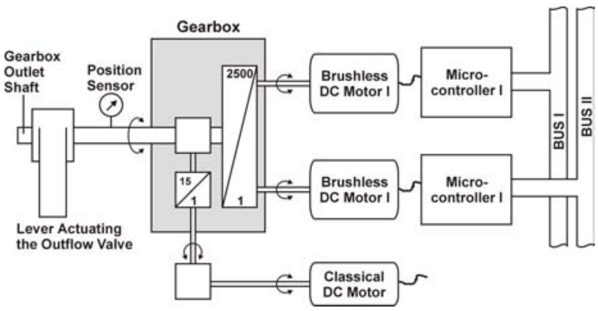


Fig. 6 Redundant DC motor drive system for the outflow valve

1999; Moseler 2000).

A detailed model of the brushless DC motor for all 3 phases is given in Moseler *et al.* (1999) and Isermann (2003). 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 ratio of inertia J_r, and the Coulomb friction torque

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

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

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

with $\nu = 2500$. The load torque of the flap is a normal 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: $U(t), I(t), \omega_r(t), \varphi_g(t)$. Using the notation

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

two equations were used for *parameter estimation*

- electrical subsystem

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

- mechanical subsystem

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

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

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

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

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

$$r_4(t) = \varphi_g(t) - \varphi_r(t)/\nu \tag{14}$$

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). Figure 7 shows measured signals, parameter estimates and residuals for 5 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 summarised in Table 7.

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 (1999) 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 8 symptoms with a rule-based fuzzy-logic diagnosis system, finally 10 different faults could be diagnosed (Moseler and Müller 2000; Moseler 2001).

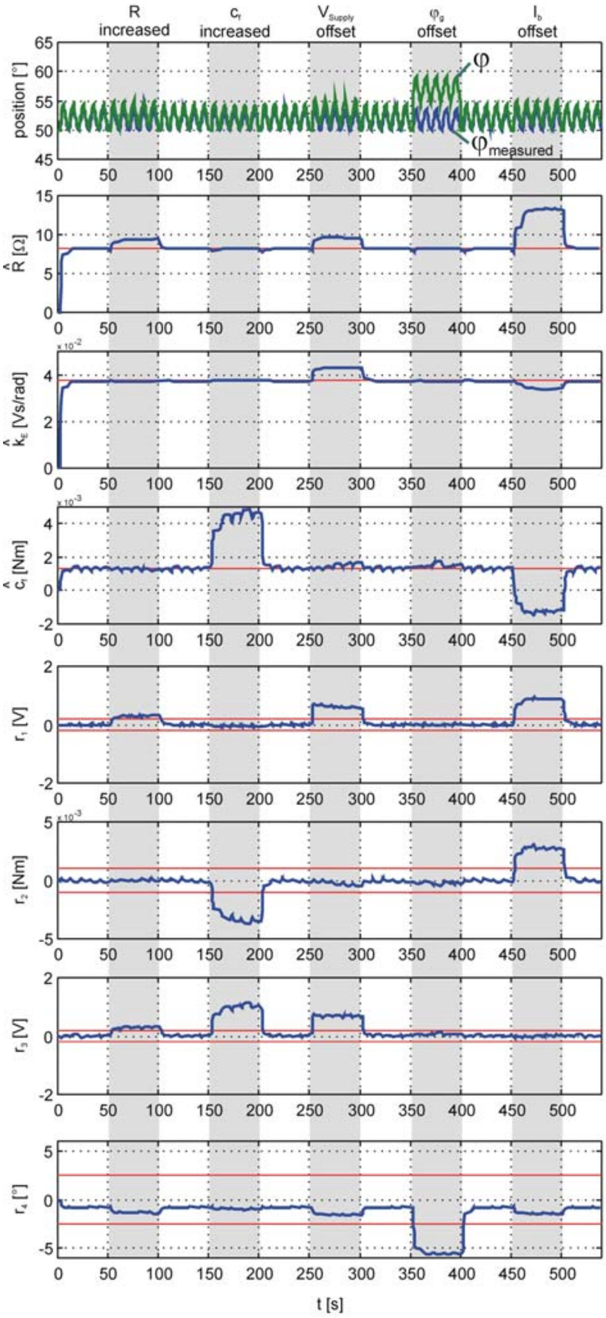


Fig. 7 Resulting symptoms from parameter estimation and parity equations by measuring $U(t)$, $I(t)$, $\omega(t)$, $\varphi_g(t)$ and $\varphi_r(t)$

Table 7 Parameter deviations and parity equation residuals for different actuator faults (0 no significant change; + increase; ++ large increase; - decrease; -- large decrease

Faults	Parameter estimates			Residual 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	--

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 4 easy accessible variables U, I and ω_r and φ_g.

4.2 Supervision of the lateral driving behaviour of passenger cars

Based on theoretical modelling of the lateral behaviour of a passenger car, the characteristic velocity is considered as a parameter determining the kind of the steering behaviour, like understeering or oversteering. This characteristic value is used to classify the behaviour with regard to normal or critical driving behaviour and such indicating also faulty behaviour, like instability.

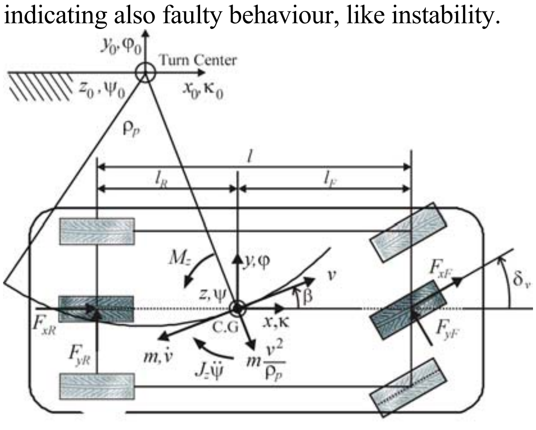


Figure 8 Scheme for modelling the lateral vehicle behaviour

Vehicle model. For deriving the lateral dynamics, a coordinate system is fixed to the center of gravity (C.G.) and Newton's laws are applied, Figure 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 bicycle model, is

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

$$\begin{bmatrix} \dot{y}(t) \\ \psi(t) \end{bmatrix} = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} \begin{bmatrix} \dot{y} \\ \psi \end{bmatrix}$$

see, e.g., Isermann (2001). The symbols are explained in Table 8. Although the bicycle model is relatively simple, it has been proven to be a good approximation for vehicle dynamics when lateral acceleration is limited to 0.4g on normal dry asphalt roads.

Table 8 Symbols: Vehicle 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	[kgm$^{2]}$
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 C.G.	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]

Stability of vehicles. Based on the state equation of the bicycle model the characteristic equation det(s**I**-**A**)=0 of the lateral vehicle dynamics becomes

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

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:

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

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

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

With the measured steering wheel angle $\delta_{st}(t)$ 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)

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

The steering angle ratio with the steering wheel angle $\delta_{st}(t)$ and the steering wheel angle $\delta_{st,0}(t)$ during neutral steering yields to

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

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

- if $v_{ch}^2 \to -/+\infty$ then neutralsteering behaviour;
- if $v_{ch}^2 > 0$ then understeering behaviour;
- if $v_{ch}^2 = 0$ then indifferent behaviour;
- if $v_{ch}^2 < 0$ then oversteering behaviour.

Figure 9 shows the different driving conditions and the stable and unstable region.

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 (18). 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 $\delta_{st} < \delta_{st,L}$, it is assumed that the driving condition is mainly a straight run, just compensating for disturbances. If $\delta_{st} > \delta_{st,L}$ cornering

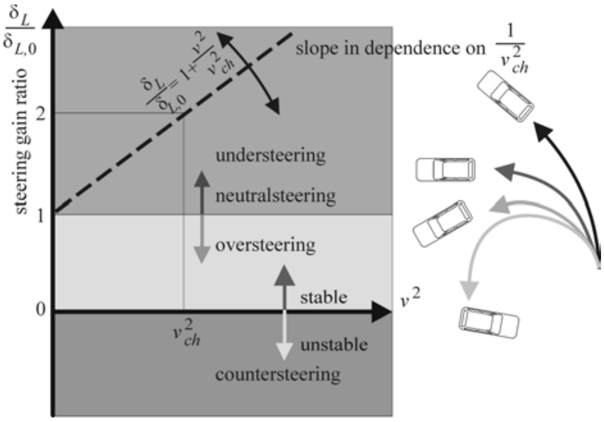


Fig. 9 Steering gain ratio in dependence on the speed v^2 and characteristic velocity v^2_{ch}

can be assumed. Then a classification of different driving situations can be made as shown in Table 9 (Börner *et al.*, 2002) with an indicator called Characteristic Velocity Stability Indicator CVSI.

Table 9 Classification of different driving conditions ($\wedge$:logical AND)

Signal processing			Driving condition		Stability	CVSI
$(\delta_{st}<\delta_{st,L}) \wedge (v^2>0)$	$\dot\psi < \dot\psi_{thres}$		Straight run	-	Stable	-1
	$\dot\psi \geq \dot\psi_{thres}$			μ-split	Unstable	0
$(\delta_{st} \geq \delta_{st,L}) \wedge (v^2>0)$	$v_{ch}^2 \geq 0$	-	Cornering	Under-steering	Stable	1
		$v^2 \gg -v_{ch}^2$		Neutral-steering	Stable	2
	$v_{ch}^2 < 0$	$v^2 \ll -v_{ch}^2$				
		$v^2 < -v_{ch}^2$		Oversteering	Stable	3
		$v^2 = -v_{ch}^2$		High oversteering	Indifferent	4
		$v^2 > -v_{ch}^2$		Breaking away	Unstable	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. Figure 10 shows the behaviour for a double lane change. After starting cornering, the vehicle shows first understeering, then neutral steering and oversteering behaviour. At t= 16.4 s and 17.8 s for a short time unstable behaviour with counter steering can be observed. Further examples are shown in Börner (2004).

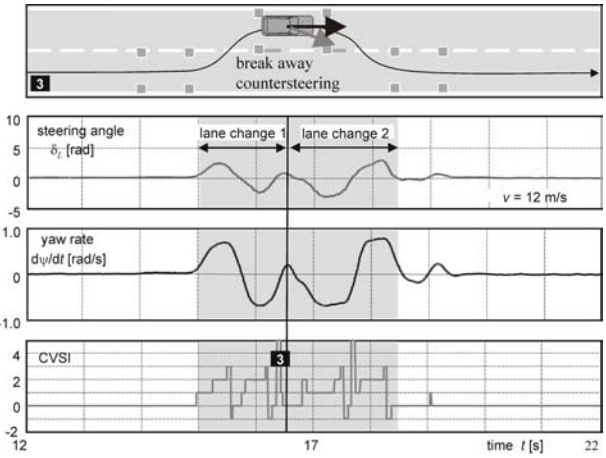


Fig. 10. Double lane change with speed v = 12 m/s: (a) steering angle; (b) yaw-rate; (c) CVSI: characteristic velocity indicator

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, residuals and symptoms. Former publications on fault detection of gasoline engines are, for example, Krishnaswami et al. (1995), Rizzoni and Samimy (1996), Isermann (2003a), Isermann (2003b), Nielsen and Nyberg (1993) or Gertler (1998).

Figure 11 shows the concept for the developed model-based fault detection and diagnosis of the complete engine, see also Kimmich et al. (2001), Schwarte et al. (2001), Schwarte et al. (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 litre, 4 cylinder, 16 valve turbo charge DI Diesel engine with a power of 74 kW and a torque of 205 Nm. The engine employs exhaust gas recirculation and a variable swirl of the inlet gas for emission reduction.

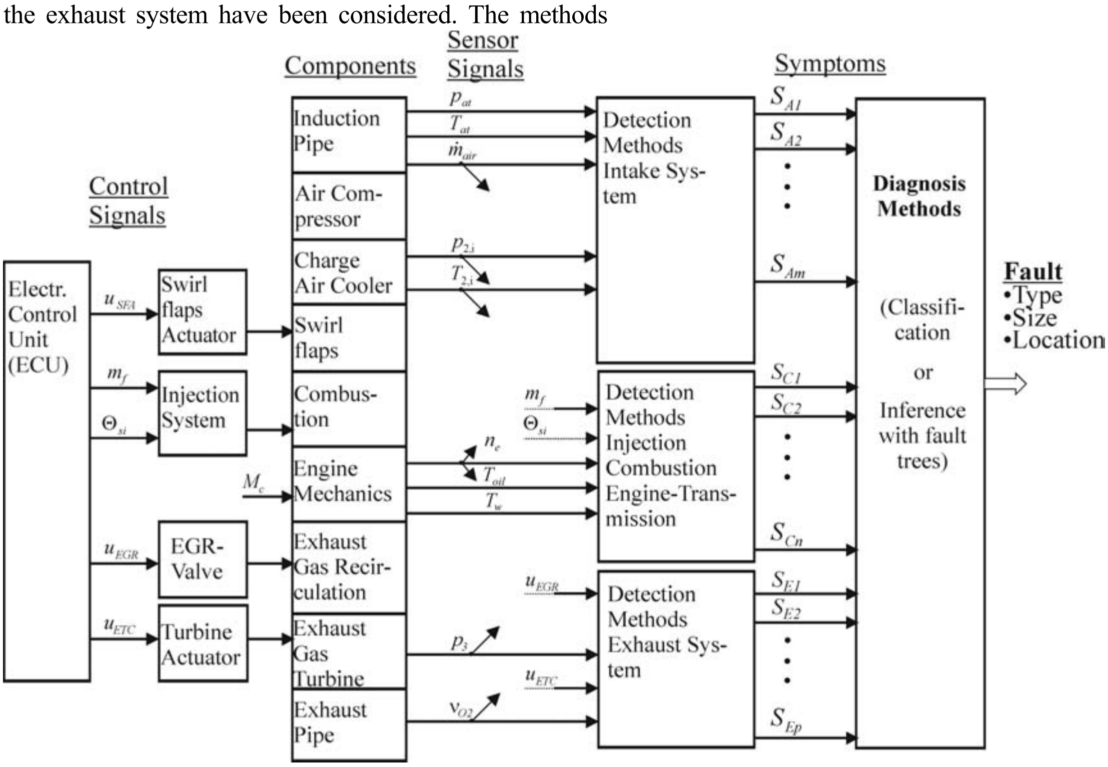


Fig. 11. Concept of a modular model-based fault-detection system of the complete combustion engine. Module 1: intake system; module 2: injection, combustion; module 3: exhaust system

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

The signal flow for the intake system is shown in Figure 13. 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. 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 modelled 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 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 result of real-time fault detection are presented in Figure 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 behaviour in order to isolate the different faults. Similar methods were developed for the other parts of the Diesel engine, (Isermann et al. 2004).

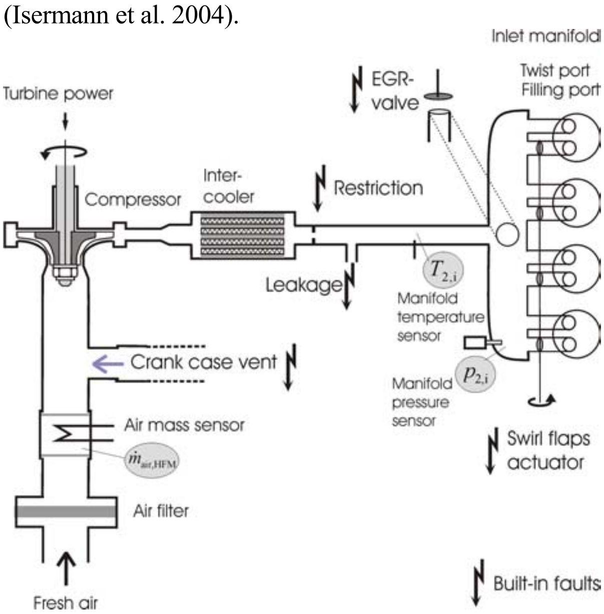


Fig. 12. Air path of the intake system with sensors and considered faults

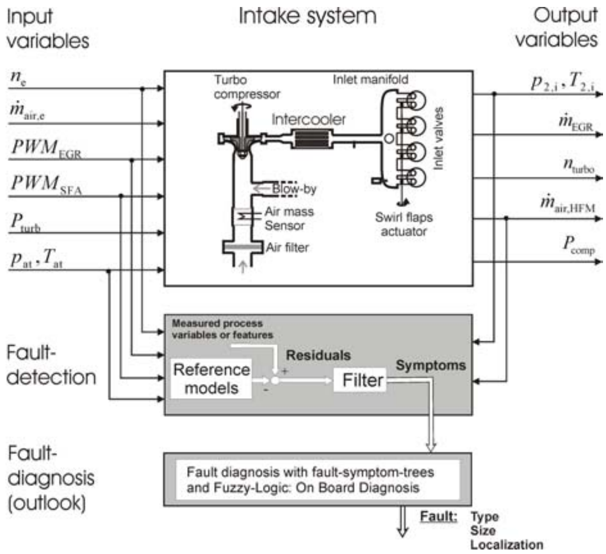


Fig. 13. Fault diagnosis structure of the intake system

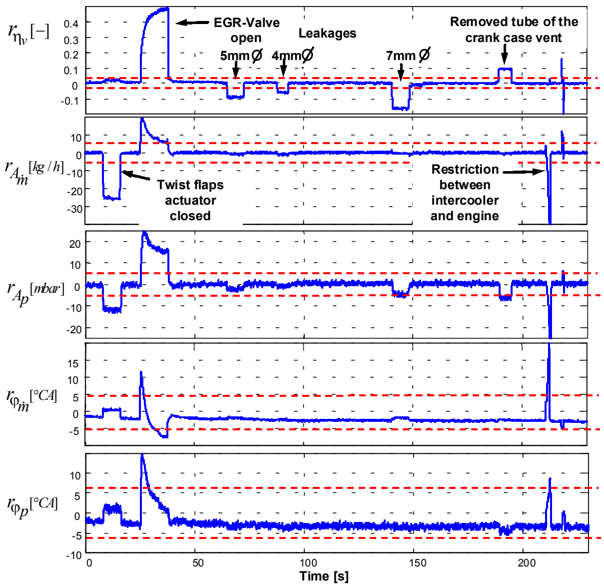


Fig. 14. Residual deflection in dependency on faults (online). 2000 min^{-1} , 130 Nm, $p_{2,i}$ = 1.5 bar, air flow 165 kg/h

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