

## Model Adjustment and Multi-Model Based Fault Diagnosis for Hydraulic Servo Axis

Marco Muenchhof\* Mark Beck\*\*

\* *Technische Universitaet Darmstadt, Institute of Automatic Control, Laboratory for Control Systems and Process Automation, Darmstadt, Germany (Tel: +49-6151-16-3114; e-mail: MMuenchhof@iat.tu-darmstadt.de).*

\*\* *Technische Universitaet Darmstadt, Institute of Automatic Control, Laboratory for Control Systems and Process Automation, Darmstadt, Germany (Tel: +49-6151-16-2314; e-mail: MBeck@iat.tu-darmstadt.de).*

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**Abstract:** This paper presents a model adjustment and a multi-model based fault diagnosis approach. Both methods are based on the same idea. A physical model of the process is altered such that it mimics the behavior of the process in the presence of certain faults. A number of these modified models, each governing a different fault condition, are evaluated and the model with the smallest output error is determined. As this model is assumed to best govern the current process dynamics, it can be used to diagnose the actual state of the process. Two variations of this idea are presented, tailored specifically to online and offline operation respectively. For online applications, multiple models with fixed parameters are evaluated in parallel, whereas for offline application, an optimization approach is employed. Here, one model with several fault size parameters is regarded and the optimal fault size parameters are determined by means of an interval halving technique. Both techniques have been evaluated at a testbed and have shown very good fault detection and diagnosis capabilities.

Keywords: Hydraulic Actuators, Fault Diagnosis, Sensor Failures, Physical Models, Optimization

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### 1. INTRODUCTION

As downtimes of manufacturing machines are quite costly, the availability of machines gains more and more attention. This also places a focus on integrated fault management capabilities, which can detect incipient faults in the system and alarm the technicians before the fault seriously affects the machines performance. The fault management system should be capable of supplying the maintenance technician with detailed information about the type, size, and location of the fault, so that the service operation can be completed in minimum time. The fundamentals of fault detection and diagnosis approaches are for example treated by Gertler [1998], Patton et al. [2000], Frank [1990], and very recently in Isermann [2006].

Mechatronic systems will more and more contain an embedded digital information processing facility, see Isermann [2003]. As this trend continues, there will be more and more hydraulic components (pressure supplies, proportional valves and axis controllers) which have integrated information processing capabilities, such as e.g. micro-controllers. Typically, the control task, for example the displacement control of the servo axis as carried out by the axis controller, does hardly take up the entire available computational capabilities. Thus one can think about integrating additional functions, such as adaptive control algorithms and fault detection, diagnosis and management functionalities. If furthermore the component is connected

to a LAN, such as Industrial Ethernet, the component can be included into and become part of a total asset management system.

In the area of fault detection and diagnosis for hydraulic systems, one can note that the predominant model-based fault detection tool is the Extended Kalman-Filter, which is for example employed by Schreiber [2003], Crepin [2003], as well as An and Sepehri [2003]. Muenchhof [2006] has shown the design of parity equation based and parameter estimation based fault detection and diagnosis approaches, which have been capable of detecting tiny incipient faults. For sensor faults, it was e.g. possible to detect offset faults in the size of roughly 1% of the maximum sensor reading.

Besides, these model based approaches, approaches employing supplementary equipment have been reported in literature. Acoustic diagnosis of a switch valve has been discussed by Ellwein and Hentschel [2004]. Infrared thermography of the hydraulic plant has been described by Ortwig and Staudt [2004]. While the use of such supplementary equipment is attractive in terms of the ease of application, it is often not desirable from an economic point of view.

Therefore, the paper at hand focuses on the fault detection and diagnosis with series instrumentation of the hydraulic servo axis. The supervision system is tailored to linear hydraulic servo axes which consist of a proportional valve

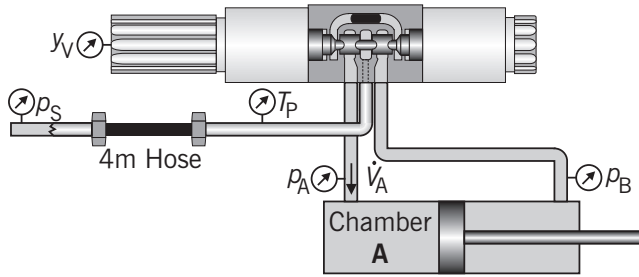


Fig. 1. Schematic Drawing of Hydraulic Servo Axis along with Sensor Location

and a hydraulic cylinder. The supervision of the pressure supply, i.e. the hydraulic pump, is not discussed in this paper, but has been treated for example by Tan and Sepehri [2001] as well as Gao and Patton [2003].

The paper is divided as follows. In Sect. 2, a physics-based model of the hydraulic servo axis is derived. This model then serves as a basis for the model-based fault detection and diagnosis methods developed in Sect. 3 and 4. The multi-model based fault diagnosis method described in Sect. 3 can be employed in online fault detection and diagnosis. Besides the model of the fault-free servo axis, a number of models governing the behavior of the plant in the presence of different faults, are evaluated. The model which best describes the behavior of the servo axis (as rated by the squared output error) is assumed to simulate the current state of the servo axis best. This approach works with a number of fixed-parameter models. As the models are hence not adjusted during the operation of the fault detection and diagnosis system, the system is real-time capable and can be employed online to supervise the state of the system.

The model adjustment approach (Sect. 4) uses an optimization approach to tune the parameters of a plant model so that the output error gets minimal. As the global plant model comprises the physics-based model of the hydraulics as well as a number of fault models, the model parameters that have been determined by the parameter optimization approach can at the same used to diagnose the hydraulic system. Although the fault detection and diagnostic system is real-time capable, it is typically not operated on-line as the computational complexity is larger than for the aforementioned multi-model based approach.

## 2. PHYSICAL MODEL OF THE HYDRAULIC SERVO AXIS

First, a model for the fault free process will be developed. A cut-away drawing of the considered hydraulic servo axis is shown in Fig. 1.

A proportional acting direct-driven valve is used to direct and throttle the fluid flow. There are four different flow path's inside the proportional valve, connecting the fluid supply and tank to the two cylinder chambers. The control edges inside the hydraulic valve are shaped such that a turbulent flow evolves even at low Reynold's numbers. The flow to and from chamber A,  $\dot{V}_A(t)$  is thus given as

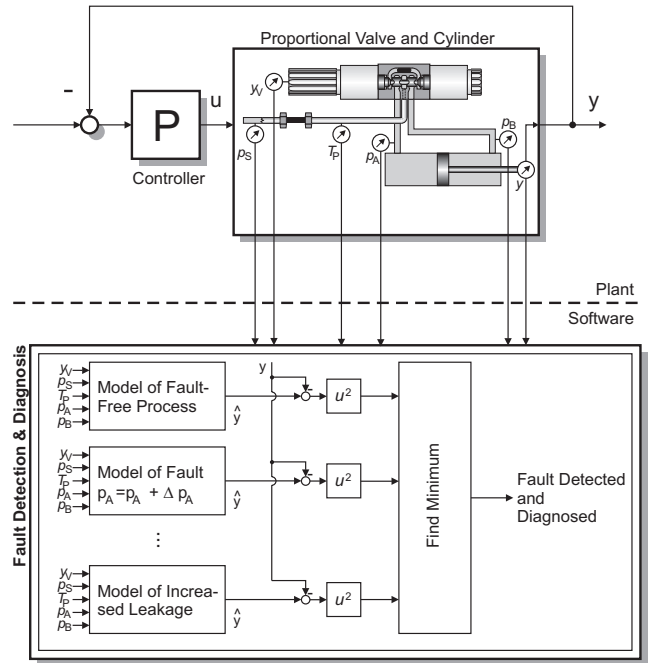


Fig. 2. Schematic Drawing of Multi-Model Based Fault Detection and Diagnosis

$$\dot{V}_A(t) = \begin{cases} b_{V1}(y_V, T_P) \sqrt{|p_S(t) - p_A(t)|} \dots & \text{for } y_V(t) > 0 \\ \dots \text{sign}(p_S(t) - p_A(t)) & \text{for } y_V(t) < 0 \end{cases} \quad (1)$$

where  $b_{V1}$  and  $b_{V2}$  are the coefficients of valve flow, which depends on both the valve spool displacement and the fluid temperature.

The valve flow depends nonlinearly on the valve spool displacement due to the design of the valve spool. In order to model this nonlinear relation with sufficient fidelity, a polynomial model of order 3 is used to capture the flow coefficient,

$$b_{V1}(y_V, T_P) = \begin{cases} a_{02}(T_P) + a_{12}(T_P)y_V(t) + a_{22}(T_P)y_V^2(t) \dots & \text{for } y_V(t) > 0 \\ \dots + a_{32}(T_P)y_V^3(t) & \text{for } y_V(t) < 0 \end{cases} \quad (2)$$

The valve flow relation consists of two separate branches, one for  $y_V(t) > 0$  where the flow path  $P \rightarrow A$  is opened and one for negative valve openings  $y_V(t) < 0$ , where the flow path  $A \rightarrow T$  is opened.

The behavior of the fluid entrapped in cylinder chamber A is governed by

$$\dot{V}_A(t) = A_A \dot{y}(t) - G_{AB}(T_P)(p_A(t) - p_B(t)) \dots - \frac{\dot{p}_A(t)(V_{0A} + A_A y(t))}{E_{0A}(T_P)} \quad (3)$$

Here,  $A_A$  is the cross sectional area of the cylinder chamber,  $G_{AB}(T_P)$  denotes the temperature-dependent flow coefficient for the laminar leakage flow between chamber A and chamber B.  $p_A(t)$  and  $p_B(t)$  are the chamber pressures,  $V_{0A}$  the so-termed dead-volume and  $E_{0A}(T_P)$  the temperature-affected bulk modulus of the oil being enclosed in cylinder chamber A. The temperature-dependent

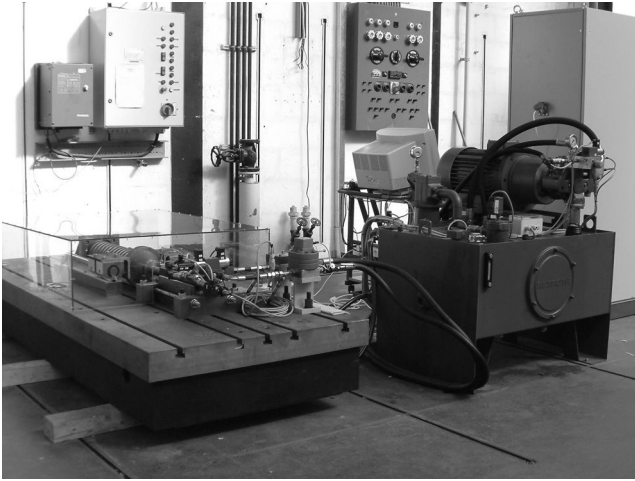


Fig. 3. View of Testbed

coefficient are linearly interpolated between a parameter set at the low temperature end of the operating range and a parameter set at the high temperature end of the operating range. These parameter sets have been determined by means of a parameter estimation from experimental data recorded at the testbed described in Sect. 3.2. The DSFI algorithm, which can be found e.g. in Isermann [1991], has been used for this task due to its simple application and numerical robustness.

Combining (1), (2) and (3) yields

$$\dot{y}(t) = \frac{1}{A_A} \left( \dot{V}_A(t) - G_{AB}(T_P) (p_A(t) - p_B(t)) \dots \dots - \frac{\dot{p}_A(t) (V_{0A} + A_A y(t))}{E_{0A}(T_P)} \right) \quad (4)$$

This model of the piston velocity is used in the following for the multi-model based fault detection and diagnosis approach as well as the model adjustment approach.

Both approaches work with models that mimic the behavior of the plant in the presence of certain faults. Thus fault models must be set up now. For process faults, one can typically insert the fault into the model by increasing or decreasing certain model parameters. For increased internal leakage e.g. one can increase the coefficient of laminar internal leakage,  $G_{AB}$  by a factor of 2 or so.

For sensor faults, it is assumed that the sensor can show both an offset fault and a multiplicative fault. An offset fault represents e.g. a drift of the zero point. A multiplicative fault on the contrary is e.g. a change in the sensor gain. Thus, a model for the sensor signal  $p_A(t)$  falsified by an offset fault  $\Delta p_A$  and a gain fault  $k_{p_A}$  is given as

$$\tilde{p}_A(t) = (1 + k_{p_A}) p_A(t) + \Delta p_A, \quad (5)$$

where the (potentially) falsified signal is denoted as  $\tilde{p}_A(t)$ .

### 3. ONLINE ALGORITHM: MULTI-MODEL BASED FAULT DIAGNOSIS

In the following, a multi-model based fault diagnosis method will be developed which is both real-time capable and computationally inexpensive and henceforth ideally suited for application in an online fault management system. Sect. 3.1 governs the theoretical development

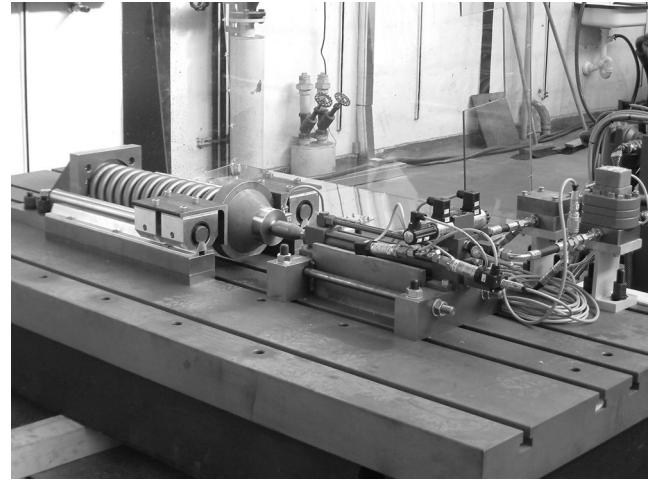


Fig. 4. View of Testbed

while Sect. 3.2 presents experimental results from the evaluation at a real testbed.

#### 3.1 Theoretical Derivation

For the online algorithm, the general setup is shown in Fig. 2. A couple of models which are all based on (4) are evaluated online with the measurements taken at the process. While one model describes the fault free case, all other models describe the behavior of the process in the presence of a certain fault.

For each sample step and each model  $i$ , the error between the model output, the estimated piston velocity, and the real measured piston velocity is determined and squared,

$$e_i^2(k) = (y(k) - \hat{y}_i(k))^2 \quad (6)$$

This squared error of each model  $i$  is then filtered with a moving average filter of length  $N$ , which has the transfer function

$$G_F(z^{-1}) = \frac{1}{N} (1 + z^{-1} + z^{-2} + \dots + z^{-(N-1)}) \quad (7)$$

For the filtered, squared errors  $e_{Fi}^2(k)$ , the minimum is determined over the entire set of models, i.e.

$$n(k) = i \text{ with } \min_i e_{Fi}^2(k) \quad (8)$$

This way, the number of the model, which over the time window from sample  $k - N$  to sample  $k$  best describes the system behavior, is determined. From this information, one can already derive the diagnosis: The system under investigation is most likely affected by the fault that was inserted into the model with number  $n(k)$ . Note that  $i = 1$  always denote the fault free case, i.e. if  $n(k) = 1$ , the system is fault-free at time step  $k$ .

#### 3.2 Evaluation at Testbed

The algorithm has been tested extensively at a real hydraulic servo axis, Fig. 3. The servo axis consists of a swash-plate axial piston pump, a direct-driven proportional valve and a differential cylinder. The cylinder works against a spring, which is used as a load simulator, Fig. 4.

Now, sensor faults of different size have been injected and it has been tested, whether the system is able to detect

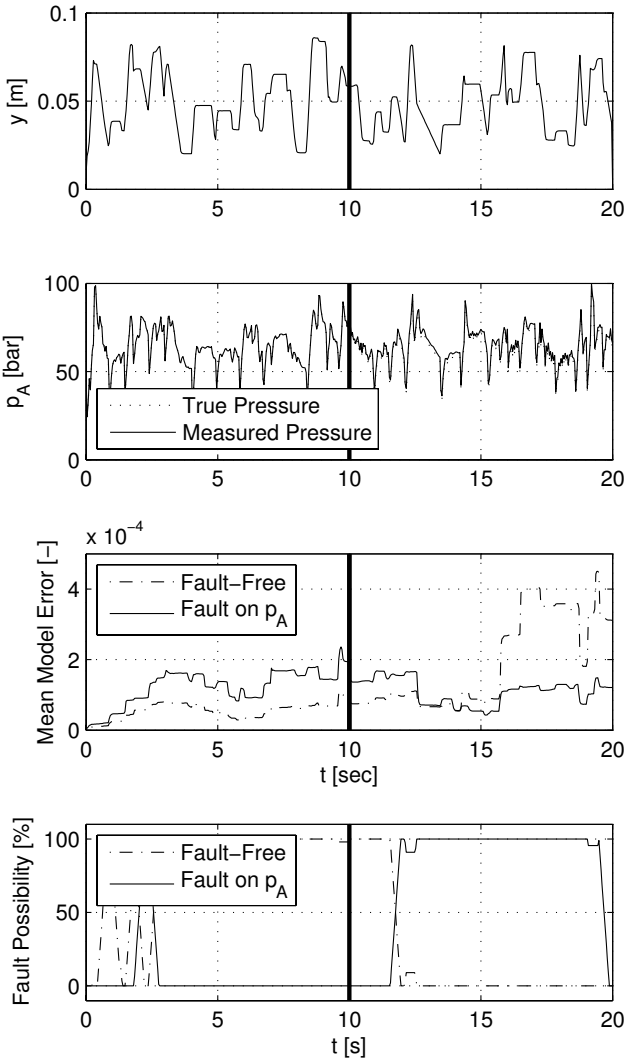


Fig. 5. Diagnostic Result for the Multi-Model Based Approach. The Thick Vertical Line Denotes the Onset of a Sensor Offset Fault  $\Delta p_A = 2$  bar at  $t = 10$  s

and diagnose the corresponding fault correctly. The first result that can be observed is that the fault detection and diagnosis system always attributes sensor faults to the correct sensor, but over the short window of time, can most often not discern offset and multiplicative faults correctly. Thus, in the following, the fault possibilities of a gain and an offset fault of the same sensor are combined into one fault possibility for this sensor.

Figure 5 illustrates the performance of the multi-model based fault detection and diagnosis system. In the topmost plot, one can see the lapse of the piston displacement  $y(t)$ , the plot below it represents the chamber pressure  $p_A(t)$ . At the time  $t = 10$ s, an offset fault of  $\Delta p_A = 2$  bar is injected. This point in time is marked by the thick vertical line in all plots. Henceforth this line marks the onset of the fault. The fault size is so small that it can hardly be seen in the plot.

The third diagram plots the filtered model error of both the fault free model and the model which mimics a positive offset fault on the pressure sensor  $p_A(t)$ . After the transients at startup of the system have died out, one

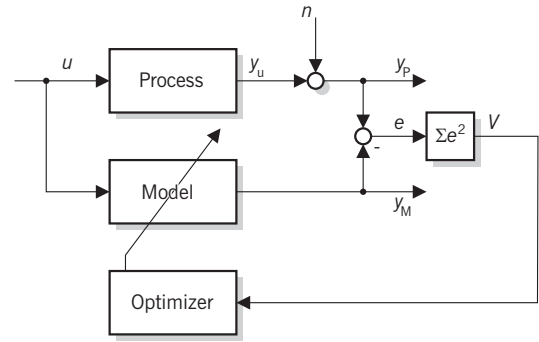


Fig. 6. Scheme of Model Adjustment Technique

can see that the filtered model error of the fault free model is always below the line for the faulty case. Shortly after the onset of the fault, the model error of the fault-free model increases and thereafter lies above the model error for the model which governs the behavior of the plant in the presence of a pressure sensor offset fault on the pressure sensor for chamber A,  $p_A(t)$ . The bottommost diagram displays the fault possibility for both the system being fault-free and the system having a sensor fault on the sensor for the chamber pressure A,  $p_A$ .

#### 4. OFFLINE ALGORITHM: MODEL ADJUSTMENT

Model adjustment describes a technique, where, by an optimization approach, several model parameters are adjusted, such that the output error between the process and the model becomes as small as possible. Sect. 4.1 describes the application of this technique to fault detection and diagnosis of a hydraulic servo axis. Sect. 4.2 complements this theoretical derivation with an experimental evaluation.

##### 4.1 Theoretical Derivation

For the model adjustment approach, the model in (4) is adjoined with fault models for all sensors and for process faults. Thus, the complete model is given as

$$\begin{aligned}
 k_y \dot{y}(t) = & \frac{1}{A_A} \left( \dot{V}_A(t) - (k_{AB} G_{AB}) (k_{TP} T_P + \Delta T_P) \dots \right. \\
 & \dots (k_{pA} p_A(t) + \Delta p_A - k_{pB} p_B(t) - \Delta p_B) \dots \\
 & \left. \dots - \frac{k_{pA} \dot{p}_A(t) (V_{0A} + A_A k_y y(t))}{E_{0A} (k_{TP} T_P + \Delta T_P)} \right)
 \end{aligned} \tag{9}$$

and

$$\begin{aligned}
 b_{V1}(y_V, T_P) = & \left\{ \begin{aligned} & a_{02}(T_P) + a_{12} (k_{TP} T_P + \Delta T_P) (k_{yV} y_V(t) + \Delta y_V) \dots \\ & \dots + a_{22} (k_{TP} T_P + \Delta T_P) (k_{yV} y_V(t) + \Delta y_V)^2(t) \dots \\ & \dots + a_{32} (k_{TP} T_P + \Delta T_P) (k_{yV} y_V(t) + \Delta y_V)^3(t) \dots \\ & \dots \text{ for } (k_{yV} y_V(t) + \Delta y_V) > 0 \\ & a_{01}(T_P) + a_{11} (k_{TP} T_P + \Delta T_P) (k_{yV} y_V(t) + \Delta y_V) \dots \\ & \dots + a_{21} (k_{TP} T_P + \Delta T_P) (k_{yV} y_V(t) + \Delta y_V)^2(t) \dots \\ & \dots + a_{31} (k_{TP} T_P + \Delta T_P) (k_{yV} y_V(t) + \Delta y_V)^3(t) \dots \\ & \dots \text{ for } (k_{yV} y_V(t) + \Delta y_V) < 0 \end{aligned} \right.
 \end{aligned} \tag{10}$$

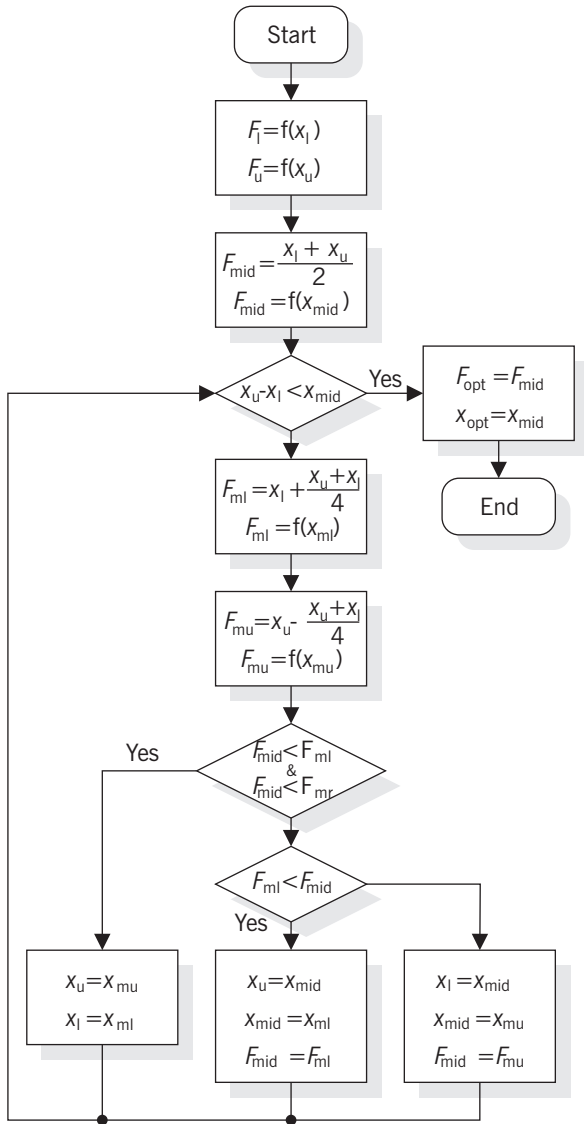


Fig. 7. Scheme of the 1D Interval Halving Optimization Algorithm: Given Lower End  $x_l$ , Upper End  $x_u$  and Desired Interval Length  $x_{min}$

Now, the individual parameters are determined by means of a parameter optimization approach. Currently, only single sensor faults are supported, thus each parameter is determined individually by a 1-D constrained search, see e.g. Vanderplaats [1998]. The cost function is given as the sum of squared error

$$e = \frac{1}{N} \sum_{k=0}^{N-1} (y(k) - \hat{y}(k))^2, \quad (11)$$

see Fig. 6. As the cost function is expected to be uni-modal, an interval halving approach is used to determine the individual fault size parameters, the interval-halving algorithm is presented in Fig. 7.

Using the optimization technique just presented, the fault model parameters  $k_y$ ,  $k_{AB}$ ,  $k_{TP}$ ,  $\Delta T_P$ ,  $k_{pA}$ ,  $\Delta p_A$ ,  $k_{pB}$ ,  $\Delta p_B$ , and  $k_y$  are determined along with the model error at the optimal fault parameter size. In the next step, the smallest of all the model errors is determined. The

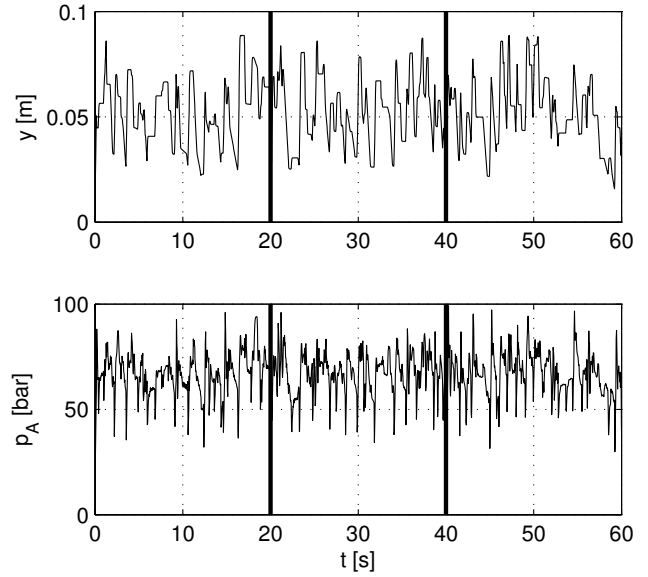


Fig. 8. Test Data for the Multi-Model Based Diagnosis Approach

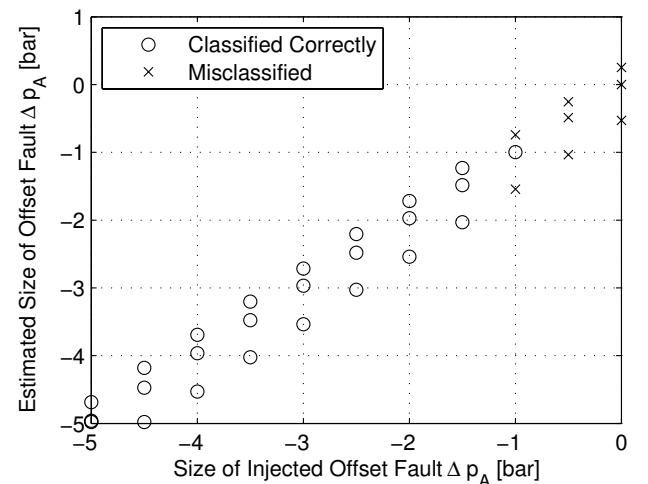


Fig. 9. Diagnostic Result for the Model Adjustment Based Diagnosis Approach

model that corresponds with this smallest model error is presumably best capturing the system behavior and thus represents the most likely fault situation.

#### 4.2 Evaluation at Testbed

For the experimental evaluation, three datasets have been recorded at the testbed. Fig. 8 shows the piston displacement profiles  $y(t)$  along with the pressure signals of the pressure sensor for chamber A,  $p_A(t)$ . The thick vertical lines denote the borders between the different data sets.

Now, sensor offset faults for the pressure sensor of chamber A,  $\Delta p_A(t)$  have been injected by altering the recorded data. Fig. 9 shows that sensor faults as small as 1 bar can be diagnosed correctly. The uncertainty in the fault size is also as small as  $\pm 0.5$  bar.

## 5. CONCLUSION AND OUTLOOK

Two fault detection and diagnosis techniques have been presented in this paper: A model adjustment and a multi-model based approach. Both methods have interesting benefits:

The multi-model based approach has the following advantages over competing fault detection and diagnosis methods as e.g. parity-equation based fault detection. First, only one plant model must be known. For many other approaches as e.g. bank of observers or parity equations, multiple models with different input/output configurations must be set up. Secondly, the multi-model based diagnosis allows to separate process faults and sensor faults, which e.g. parity equation based methods typically cannot achieve. In addition, no thresholds must be defined. The separation between the fault-free and the faulty state of the feature can easily be achieved by comparing the output error of the fault-free model with the output error of all faulty models. By this approach, the operating-point dependent variation of the model fidelity is intrinsically included as the fault-free model is considered as a reference for the maximum achievable model fidelity in the fault free case.

The model adjustment approach shows similar advantages, its main feature however is that not only the type of fault, but also its size can be determined quite accurately. Knowledge of the fault size is extremely important for a subsequent fault management system as based on the fault size, different remedial actions might have to be triggered ranging from a scheduled maintenance service up to the immediate emergency shutdown of the plant. Furthermore, this approach does neither require the design of multiple models with different sensor configurations nor does it require the definition of thresholds. It can differ between sensor faults and process faults.

In the future, this approach shall be extended to the detection and diagnosis of multiple faults. For the multi-model approach one can think about models mimicking several faults at the same time. For the model adjustment approach, one should employ an  $n$ -dimensional optimization technique, as e.g. the steepest descent technique. Furthermore, one should approximate this complex model by a model which is linear in its fault size parameters as this would allow the use of direct optimization techniques such as the method of Least Squares. This would not only speed up the optimization itself, but would also allow the model adjustment technique to be employed online.

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