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# Kalman-based strategies for Fault Detection and Identification (FDI): Extensions and critical evaluation for a buffer tank system

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A B S T R A C T

This paper is concerned with the application of Kalman filter based methods for Fault Detection and Identification (FDI). The original Kalman based method, formulated for bias faults only, is extended for three more fault types, namely the actuator or sensor being stuck, sticky or drifting. To benchmark the proposed method, a nonlinear buffer tank system is simulated as well as its linearized version. This method based on the Kalman filter delivers good results for the linear version of the system and much worse for the nonlinear version, as expected. To alleviate this problem, the Extended Kalman Filter (EKF) is investigated as a better alternative to the Kalman filter. Next to the evaluation of detection and diagnosis performance for several faults, the effect of dynamics on fault identification and diagnosis as well as the effect of including the time of fault occurrence as a parameter in the diagnosis task are investigated.



## 1. Introduction

Fault Detection and Identification (FDI, Isermann & Ballé, 1997) deals with the timely detection and diagnosis of anomalies in processes or systems and has gained attention since the 1990s. Several philosophies have been adopted in the past, leading to a wide range of available tools (Venkatasubramanian, Rengaswamy, & Kavuri, 2003; Venkatasubramanian, Rengaswamy, Kavuri, & Yin, 2003; Venkatasubramanian, Rengaswamy, Yin, & Kavuri, 2003). A rough classification of methods can be made according to whether the applied methods are deductive or inductive in nature. A typical deductive method will be based on first-principles knowledge while inductive methods are based on recognition of patterns in process data sets, with roots in statistical theory (e.g. Principal Component Analysis) or Artificial Intelligence (e.g. Artificial Neural Networks). Deductive methods, due to their assumption on available first principles knowledge, tend to be more rigorous and accurate in nature. However, the cost of accurate knowledge or models may be prohibitive so that only inductive methods may be achievable in practice. Quite naturally, hybrid approaches are applicable, e.g. when first principles knowledge is available to some extent but not for the whole system. Another way of categorizing FDI methods may be based along the internal representations used. For sure, quantitative representations are the most popular. The Kalman filter adopted for FDI in Prakash, Patwardhan, and Narasimhan (2002) and further extended in this work is a quantitative method in the deductive category. Principal Component Analysis is a quantitative method in the inductive category (Joliffe, 2002). A smaller segment of FDI methods is based on qualitative representations. Examples of such methods in the deductive category are Signed Directed Graphs (SDGs, Maurya, Rengaswamy, & Venkatasubramania, 2004) and qualitative reasoning (Forbus, 1984; Kuipers, 1994). In the inductive category, a large variety of time series trending methods is available (e.g., Akbaryan & Bishnoi, 2001; Bakshi & Stephanopoulos, 1994; Charbonnier, Garcia-Beltan, Cadet, & Gentil, 2005; Dash, Maurya, & Venkatasubramanian, 2004; Flehmig, Watzdorf, & Marquardt, 1998; Villez, 2007), yet little consensus exists on their respective strengths and weaknesses.

The presented work is a result of an ongoing project on state awareness for complex systems. The ultimate aim is to install tools for proper identification of potentially harmful situations in safety-critical systems. This aim fits into a larger vision on design of resilient systems, i.e. systems that only degrade gradually or gracefully when subject to series of harmful events (Rieger, Gertman, & McQueen, 2009). In this contribution, we focus on the extension and critical evaluation of an existing method for Fault Detection and Identification (FDI) which is based on the Kalman filter. This methods finds itself in the deductive-quantitative section of the FDI

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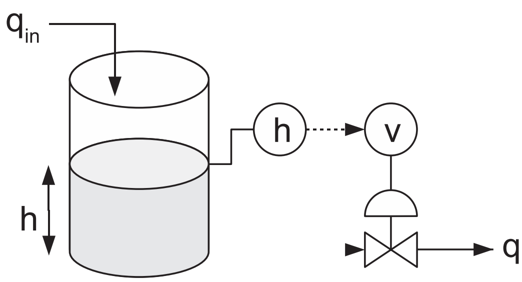


**Fig. 1.** Scheme of the simulated tank system.

methods. This method has been tested successfully for fault detection and diagnosis (Prakash et al., 2002). In particular, the method has been shown to allow proper detection and diagnosis of biases in different actuator and sensor locations as well as correction of the on-line model predictive control (MPC) scheme for identified faults (Prakash, Narasimhan, & Patwardhan, 2005). However, using only bias faults and the assumption on linearity may be considered limiting. This study therefore concentrates on (1) the extension of the method to allow the separate identification of stuck behavior, stiction, bias and drifts in sensors and actuators and (2) the evaluation of the method on both a non-linear system as well as its linearized version. As such, the simulation study allows to evaluate whether the method is applicable for non-linear systems. In what follows, Materials and Methods will be explained first. Then, results will be shown with broader discussions in separate sections. Finally, the most important conclusions are summarized in the last section.

## 2. Materials and methods

### 2.1. Benchmark simulations

Two models are used to benchmark the developed methods for FDI. Both are models of a buffer tank with a pipe connected at the bottom of the tank and with one end open to the atmosphere. The pipe is equipped with a valve. Fig. 1 shows a scheme of the system. A feedback PI controller adjusts the valve position to achieve the setpoint for the tank level based on the measurement of the tank level. One of the models is a non-linear and more realistic version of such a system. The other is the linearized version of this model, obtained by linearization around the nominal operating point. The following paragraphs explain the two models.

#### 2.1.1. Non-linear system

The open-loop system can be written as a Differential Algebraic Equation (DAE) with the tank level ($h$) as the dynamic state and the outflow rate ($q_{out}$) as the algebraic state. The valve position ($v$) is a manipulated input and the inflow rate ($q_{in}$) a disturbance input. Because the algebraic equation can be solved analytically, one can rewrite the open-loop system model as a single Ordinary Differential Equation (ODE) (Appendix A). The steady-state nominal operation is defined by the tank level ($h_o = 10\,\mathrm{m}$) and valve opening ($v_o = 50\%$), from which the corresponding steady state mean inflow rate can be computed ($q_{in,o} = 5.36\,\mathrm{m^3/s}$). All simulations are started with this steady state condition. All parameter values of the nonlinear model are listed in Appendix B.

#### 2.1.2. Linear system

To obtain the second benchmark system, the nonlinear model was linearized by means of evaluating the derivatives at the nominal operating point (Appendix C). For this linearized system, the use of the (linear) Kalman filter is theoretically optimal. The results obtained with this linearized system will function as a reference for evaluation of the results obtained in the non-linear case.

#### 2.1.3. Introducing faults and noise

To test the FDI strategy, several fault classes were simulated for both systems. In this paper, we consider a fault type a kind of symptomatic behavior, irrespective of its location. A fault class is defined as the unique combination of fault location and fault type. The simulated fault types are stuck behavior, stiction, bias and drift. These four fault types are introduced in two locations, namely the valve position and the tank level measurement. This leads to 8 different fault classes. Stiction, particularly in valves, has been shown to be relevant in an industrial context (Choudhury, Thornhill, & Shah, 2005; Srinivasan & Rengaswamy, 2008). However, its identification in a context where other faults are possible has not been considered yet. With $u(t)$ the valve position signal delivered by the controller, $u_f(t)$ the corrupted valve position, $t_f$ the time of fault occurrence and $\delta$ the fault parameter, the different models for the valve faults are as follows:

$$
\begin{array}{llll}
\text{No fault:} & u_f(t) & = u(t) & \\
\text{Stuck:} & u_f(t) & = u_f(t-1) & \\
\text{Stiction:} & u_f(t) & = u(t) & |h(t)-h_f(t-1)| > \delta \\
 & & = u_f(t-1) & |h(t)-h_f(t-1)| \leq \delta \\
\text{Bias:} & u_f(t) & = u(t)+\delta & \\
\text{Drift:} & u_f(t) & = u(t)+\delta \cdot \dfrac{(t-t_f)}{100\,\mathrm{s}} &
\end{array}
\quad (1)
$$

For the sensor, the equivalent models are obtained by replacing $u(t)$ and $u_f(t)$, with the true tank level, $h(t)$, and the corrupted tank level measurement, $h_f(t)$, respectively. It is noted here that the bias and drift fault types are additive while the stuck and stiction faults are non-additive. This has important implications for fault identification as will shown further.

The resulting corrupted signals ($u_f(t)$, $h_f(t)$) as well as the input flow rate ($q_{in,o}$) are subjected to white noise to obtain the actual tank level measurement, the actual valve position and the actual input flow rate ($y(t)$, $v(t)$ and $q_{in}(t)$) as follows:

$$
\begin{array}{ll}
y(t) = h_f(t) + e_1, & e_1 \sim N(0, \sigma_1^2) \\
v(t) = u_f(t) + e_2, & e_2 \sim N(0, \sigma_2^2) \\
q_{in}(t) = q_{in,o} + e_3, & e_3 \sim N(0, \sigma_3^2)
\end{array}
\quad (2)
$$

Appendix B lists the applied values for the noise standard deviations ($\sigma_1$, $\sigma_2$ and $\sigma_3$).

#### 2.1.4. Simulated scenarios

To make sure that fault detection and diagnosis results are independent of other faults, several short scenarios are simulated rather than a single process history. Both the nonlinear and linear system are simulated repeatedly for 200 s. This is done for combinations of several fault scenarios, which describe the simulation of faults, and setpoint scenarios, which describe the time profile of the tank level setpoint.

*Fault scenarios*. All faults are introduced at 101 s in the simulation. The stiction, bias and drift faults are introduced with three different parameter values, namely 5, 10 and 15 % of the value at nominal operating point. A faultless scenario is also simulated. A total of 21 fault scenarios thus results. Table 1 summarizes these scenarios and provides a fault class index (0–8) for all the fault classes.

*Setpoint scenarios*. Each of the above fault scenarios is repeated for two different setpoint scenarios. In the first scenario, SP1, a setpoint change of 10% is introduced at the start of the simulation (1 s). In these cases, the controller dynamics have settled by the time that the fault is introduced. In the other scenario, SP2, the same setpoint change is introduced at 101 s in the simulation, along with the intro-