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Sensor bias detection, isolation, and estimation in a subsea pump system.

Rafael D. Oliveira[a], Halvor A. Krog[a], Galo A. C. Le Roux[b], Johannes Jäschke[a]

[a] *Department of Chemical Engineering, Norwegian University of Science and Technology (NTNU), Trondheim, Norway*
[b] *Department of Chemical Engineering, University of São Paulo, São Paulo, Brazil*
johannes.jaschke@ntnu.no

Abstract

Subsea pump systems are subject to many possible faults and monitoring typically relies on the measurements of key process variables. However, the measurements themselves may be subject to faults like e.g., bias. In this work, a method that combines fault detection and isolation, observability analysis and state estimation is presented and tested on a simulated pump system. The results indicate that a state estimator with correct information about which sensor has drifted gives lower estimation error than a state estimator that does not consider bias. Furthermore, we show that it is impossible to estimate the bias on all sensors simultaneously due to observability issues of the augmented system.

Keywords: Sensor bias, Fault detection, Subsea pump, Fault isolation, Sensor drift.

1. Introduction

Subsea pumping systems operate in harsh environments for long periods, making the maintenance of these pumps challenging and costly. Condition monitoring is crucial to keep these subsea pumps running for long periods and to reduce the possibility of accidents. The pumps are subject to several potential faults, and it is desirable to use measurements to detect if something is going wrong. However, the sensors that provide these measures are also susceptible to faults (e.g., gross errors). These gross errors arise from sensors malfunctioning and can significantly impact the monitoring and controlling of the subsea pump.

Given the long operation times of subsea pumps, the long-term faults (e.g., bias) are more challenging to detect than other abrupt changes. It is desirable to detect and isolate these biases as soon as possible and, if practicable, estimate their magnitude. Approaches to deal with these sensor biases can be classified as passive or active. The passive methods apply robust estimators like M-estimators, robust Kalman Filter (KF), and robust Moving Horizon Estimation (MHE) (Siddhartha et al., 2022). Passive methods efficiently handle gross errors, but no information about the bias's location and size is generated. The location of the gross errors is a valuable information for maintenance and process monitoring. On the other hand, active methods try to estimate these biases, usually representing the bias as a new time-dependent continuous parameter on the state estimation problem (Gatzke & Doyle III, 2002). However, observability problems usually arise (Gatzke & Doyle III, 2002).

In this paper, we propose to combine fault detection and isolation (FDI) methods, observability analysis and state estimators in the context of a subsea pump system. In our methodology, i) FDI is used to identify sensors with bias. ii) Then an observability analysis is performed to check if it is possible to estimate that bias, and iii) then the state estimator is extended with a bias parameter to be estimated. The FDI reduces the number of biases to be estimated, and the observability analysis assurances that the bias can be estimated without worsening the state estimator's performance. This illustrates how attempting to estimate sensor bias without any *a priori* information of which sensors are failing is impractical and how combining FDI with state estimators can improve the estimation significantly. Furthermore, a Monte Carlo analysis is performed to show the advantages and limitations of that approach in multiple scenarios.

2. Case study: Subsea pump system

We consider a simple subsea booster pump system, as shown in Figure 1. A mixture of oil and water comes from the reservoir at pressure p_1. The pump runs with a variable speed drive (VSD) at ω rpm, which produces a specific head, H. Given the density of the fluid, ρ, one can calculate the pressure at the outlet of the pump, p_2. The pressure p_3 is determined by downstream facilities (oil platform). The choke valve has an opening of Z %. The three pressures are measured, and a Venturi flowmeter measures the pressure drop over an internal orifice (not shown).

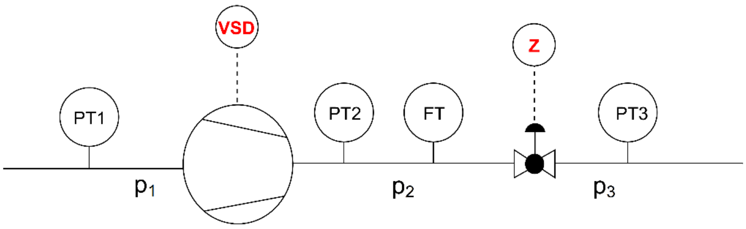

Figure 1: The subsea booster pump with its installed sensors. FT is a Venturi flowmeter.

2.1. Pump model

Sensor bias is a phenomenon that typically takes place in the timescale of months and years. The pressure and density changes in the reservoir are on the same timescale, and we assume the pressure on the oil platform has the same trend as the reservoir pressure. On the other hand, phenomena such as transient flow regimes happen almost instantly in the timescale of seconds. This motivates the use of a quasi-steady state model, where changes in the reservoir and p_3 are modelled dynamically and the pump is modeled in steady-state (and therefore the time-subscript is $k+1$ on both sides of the equality sign in (4)-(6)). It is assumed that p_1 and p_3 decreases at the same rate, hence, they have the same parameter $\theta_{P,1}$. The faultless system is described by:

$$p_{1,k+1} = p_{1,k} + \theta_{P,1}\Delta t + w_{p_1,k} \tag{1}$$

$$\rho_{k+1} = \rho_k + \theta_\rho \Delta t + w_{\rho,k} \tag{2}$$

$$p_{3,k+1} = p_{3,k} + \theta_{P,1}\Delta t + w_{p_3,k} \tag{3}$$

$$p_{2,k+1} = p_{1,k+1} + \rho_{k+1} g H_{k+1} + w_{p_2,k} \tag{4}$$

$$q_{k+1} = C_v Z_{k+1} \sqrt{\frac{p_{2,k+1} - p_{3,k+1}}{\rho_{k+1}}} + w_{q,k} \tag{5}$$

where the head at time k, H_k, is found by using the so-called pump curve.

$$H_{k+1} = \theta_{H_0}\omega_{k+1} + \theta_{H_1} q_{k+1}\omega_{k+1} + \theta_{H_2} q_{k+1}^2 \tag{6}$$

The states are $\boldsymbol{x}_k = \left[p_{1,k}, p_{2,k}, p_{3,k}, \rho_k, q_k\right]^T$ and the state-propagation equations (1)-(5) can be written in the form of $\boldsymbol{x}_{k+1} = \boldsymbol{f}(\boldsymbol{x}_k, \boldsymbol{u}_{k+1}, \Delta t) + \boldsymbol{w}_k$. The stochastic process noise is defined as $\boldsymbol{w}_k = \left[w_{p_1,k}, w_{p_2,k}, w_{p_3,k}, w_{\rho,k}, w_{q,k}\right]^T \sim (\boldsymbol{0}, \boldsymbol{Q}_k)$. The process noise distribution is assumed to be constant at $\boldsymbol{w}_k \sim \mathcal{N}(\boldsymbol{0}, \boldsymbol{Q})$ where $\boldsymbol{Q} = 10^{-5}\boldsymbol{I}$. The parameter values are $\boldsymbol{\theta} = \left[\theta_{P,1}, \theta_\rho, \theta_{H_0}, \theta_{H_1}, \theta_{H_2}, g, C_v\right] = [-5.0, 5.0, 3.51 \times 10^{-5}, 3.29 \times 10^{-4}, -0.01, 9.8 m/s^2, 47.50\ m^3/h]^T$,where g is the gravitational constant and C_v is the valve constant. The remaining parameters describe the evolution of pressure and density in time. The initial conditions for all the simulations were $\boldsymbol{x}_0 = [50.0\ bar, 64.5\ bar, 51.0\ bar, 700\ kg/m^3, 136.6\ m^3/h]^T$ and $\boldsymbol{u}_0 = [65\ \%, 3500\ rpm]^T$. When there is no bias in the sensors, the sensor equations are:

$$\boldsymbol{y}_k = \boldsymbol{h}(\boldsymbol{x}_k) + \boldsymbol{v}_k = \left[p_{1,k}, p_{2,k}, p_{3,k}, \frac{\rho_k(1-\beta^4)}{2}\left(\frac{4Q_k}{\pi d^2 C\epsilon}\right)^2\right]^T + \boldsymbol{v}_k \tag{7}$$

where $C = 1.01$ is the flow coefficient, $\epsilon = 1$ is the expansibility factor, $d = 0{,}0525mm$ is the Venturi throat diameter, $D = 0{,}154m$ is the internal pipe diameter and $\beta = d/D$. The measurement noise is distributed as $\boldsymbol{v}_k \sim \mathcal{N}(\boldsymbol{0}, \boldsymbol{R})$, where $\boldsymbol{R} = diag([0.1035, 0.1035, 0.1035, R_{venturi}])$.

2.2. Pressure sensor bias

Sensor bias is a constant systematic error in measurement and sensor drift is a time-varying bias in the sensor. Hence, the measurement equation (7) must account for these biases and drift in the following manner, where $\boldsymbol{y}_k^d$ is the bias/drift value at time k and $\boldsymbol{y}'_k$ is the measurement equation with bias/drift:

$$\boldsymbol{y}'_k = \boldsymbol{y}_k + \boldsymbol{y}_k^d = \boldsymbol{h}(\boldsymbol{x}_k) + \boldsymbol{v}_k + \boldsymbol{y}_k^d \tag{8}$$

To estimate the bias/drift, we augment the state vector and model the bias/drift as a random walk. The augmented model is now given by

$$\boldsymbol{x}_{k+1}^a = \left[\boldsymbol{x}_{k+1}, \boldsymbol{y}_{k+1}^d\right]^T = \left[\boldsymbol{f}(\boldsymbol{x}_k, \boldsymbol{u}_{k+1}, \Delta t), \boldsymbol{y}_k^d\right]^T + \left[\boldsymbol{w}_k, \boldsymbol{w}_{y^d,k}\right]^T \tag{9}$$

where $\boldsymbol{w}_{y^d,k} \sim \mathcal{N}(\boldsymbol{0}, \boldsymbol{Q}_{\boldsymbol{y}})$ is the distribution describing the steps of the random walk.

3. Combining fault detection and observability analysis to state and bias estimation.

The simultaneous estimation of states and biases in all the sensors simultaneously can make the system non-observable. To avoid these problems, this work combines FDI methods and observability analysis with state estimation. Figure 2 illustrates the methodology. The first step consists of the residual generation. The measurement (y'_k), which may have a bias or drift, is compared to the model's predicted measurement ($\hat{y}_k$). Then this residual is evaluated by a statistical test that is aimed in deciding if the system is fault-free or which sensor has drifted. After that, an observability analysis is performed to evaluate if the identified bias can be estimated. In the positive case, a new term is included on the state estimator as described in section 2.2 to track the bias/ drift on the failing sensor. Otherwise, the standard state estimation is performed without adding additional bias terms.

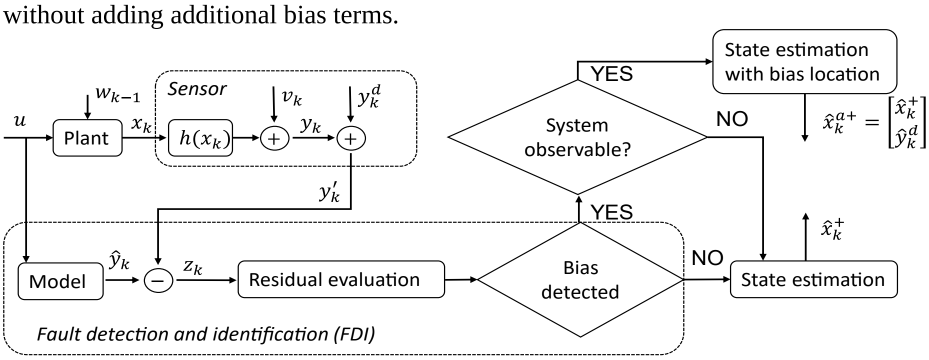

Figure 2: Conceptual flowsheet of how FDI-technique is used to update the structure of the state estimator.

3.1. Residual evaluation for bias detection

Three residuals are made, one for each pressure sensor, which consists of the difference between the model prediction and the measurement. Assuming a perfect model, it is possible to identify a bias in the pressure measurements since these residuals should be zero mean in a normal operating condition and different from zero when a bias occurs. To evaluate if the residuals are different from zero, the statistical method called cumulative sum control chart (CUSUM) was used (Blanke, 2016). A Gaussian distribution was assumed to represent the residual distribution ($\mathcal{N}(\mathbf{0}, \boldsymbol{R})$), and any deviation higher than five times the standard deviation would correspond to a fault.

3.2. State estimation and Observability analysis

We used the Unscented Kalman filter (UKF) to obtain the optimal estimate of the true state and bias (Simon, 2006, ch. 14). The bias terms were included on the UKF as time-dependent continuous parameter as described in section 2.2. The concept of observability tells us if we can uniquely determine the state given some measurements, which is a requirement for state estimators to work. For linear systems, observability can be checked by verifying if the observability matrix has full rank. See Simon (2006, ch. 1.7.2) for a definition of the observability matrix and a discussion about observability for linear systems. In our work, we linearized the model and checked the rank of the observability matrix for the linearized model. If the (augmented) system is not observable, we did *not* include the bias term in the state estimator and used the fault-free estimator as Figure 2 shows.

4. Results

The results section is divided into two parts. First, in section 4.1, an illustrative simulation shows how a previous bias detection and isolation step can improve the state estimation process. Then, in section 4.2, a Monte Carlo analysis is performed to evaluate the method's performance in different scenarios.

4.1. Estimator with information of bias location

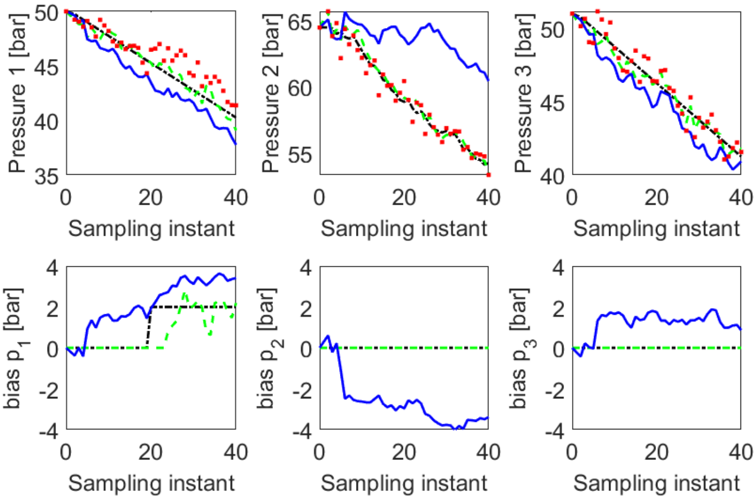

Figure 3- Comparison of true state (black), pressure measurements (red) and the estimates using UKF_b (blue) and UKF_{fdb} (green). Bias was introduced on the measurements of sensor PT1.

The model described in Section 2 was solved for a time window of 40 samplings. After 20 samples, a constant bias of 2 bar is added to the pressure sensor one (PT1). Two methodologies are compared in this scenario; first, the UKF with bias estimation (UKF_b), where the estimators try to estimate the bias on the three sensors since the beginning of the window. Hence, the augmented state dimension is $5 + 3 = 8$ through the entire time.

Second, our proposed method described in Section 3 is applied (UKF_{fdb}). Here, the state dimension is 5 before sampling time 20 and after a successful FDI and observability procedure it is 6. The results of the simulation is presented in Figure 3. The results indicate that the observability problems of adding new bias parameters to be estimated arise even for a small system like the subsea pump. UKF_b fails to estimate the states and bias in all three sensors, even before the bias is added to the measurements on sensor PT1. In fact, the observability analysis showed that the states are non-observable when three bias terms are included on the estimator.

However, when just one bias term is included on the estimator, the states and the bias are observable. This explains why the UKF_{fdb} could obtain a good estimate of the states and the bias on sensor PT1. UKF_{fdb} had a slight delay in detecting the bias on sensor PT1. After that, the observability is verified, and the information on which sensors are failing is sent to the state estimator.

4.2. Monte Carlo analysis

In order to perform a comprehensive analysis of the methodology, a Monte Carlo analysis was performed. This study compared three approaches: UKF_b, $UKFfd_b$ and the “standard” UKF without bias estimation. All the simulations started from the same initial condition, with 100 samplings as a time window. Three hundred random samples of different simulation features were used: time to insert the bias (between 10 and 80 samples), the magnitude of the bias (-2 bar to 2 bar), control profile (pump speed and valve opening), sensor location of the bias (sensor 1, 2 or 3) and bias or drift. The results of the simulations are summarized in Table 1.

The results show that the UKF_b has poorer performance than the UKF. The system's observability must be checked before including new bias parameters to be estimated. The standard UKF is the best option in cases of non-observable states. However, when a fault detection and isolation method is applied, there is no need to include a bias term in the UKF for each sensor. Instead, only after the bias is detected a new term can be added to the UKF. The UKF_{fdb} had a better performance in terms of state estimation. Besides that, it can also provide a reasonable estimate of the bias in the sensors, which is a valuable information for pump system monitoring.

Table 1: Root-mean-square error states and bias over 300 simulations. * is "sampling instances".

			RMSE						
	Bias correctly Located [%]	Average delay [*]	bias [bar]	p_1 [bar]	p_2 [bar]	p_3 [bar]	ρ [kg/m^3]	Q [m^3/h]	H [m]
UKF	-	-	-	0.74	0.77	0.75	24.97	2.54	3.15
UKF_b	-	-	4.89	2.32	3.57	1.92	273.61	2.40	3.08
UKF_{fdb}	86.00	14.96	0.52	0.42	0.41	0.44	10.86	2.58	3.21

5. Conclusion

An approach to monitor and estimate sensor bias on subsea booster pump system was numerically evaluated. The results suggest that estimating sensor bias without any *a priori* information about which sensors are failing is impractical. Therefore, combining fault detection and observability analysis techniques with sensor estimators can improve the estimation significantly and provide helpful information for system monitoring. A more thorough structural and local observability check should be applied in future works.

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