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# Early Pack-Off Diagnosis in Drilling Using an Adaptive Observer and Statistical Change Detection

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**Abstract:** Pack-off is a partially or complete blocking of the circulation flow in oil and gas drilling, which can lead to costly delays. Early detection and localization of a pack-off is crucial in order to take necessary actions avoiding downtime. This incident will affect physical friction parameters in the well. A model-based adaptive observer is used to estimate these friction parameters as well as flow rates. Detecting changes to these estimates can then be used for pack-off diagnosis, which due to measurement noise is done using statistical change detection. Isolation of incident type and location is done using a multivariate generalized likelihood ratio test, determining the change direction of the estimated mean values. The method is tested on simulated data from the commercial high-fidelity multi-phase simulator OLGA, where three different pack-offs at different locations and with different magnitudes are successfully detected at an early stage and with low false alarms.

*Keywords:* Fault diagnosis, adaptive observer, multivariate statistical change detection, oil and gas drilling, pack-off

## 1. INTRODUCTION

The basic concept of oil and gas drilling is to use a rotating drillstring with a drill bit, crushing the formation and circulating out this mass through the annulus surrounding the drillstring, as shown in Fig. 1. If the formed cuttings are not properly transported out of the well, or if parts of the wellbore collapses due to an unstable formation, the well can start to *pack off*, reducing circulation capabilities. If no action is taken the drillstring can become stuck, which will result in expensive delays. Early diagnosis of a pack-off is thus instrumental in maintaining proper hole cleaning, avoiding expensive non-productive time.

Advances in drilling methods and technology, such as *managed pressure drilling* (MPD), bring along improved instrumentation. One such improvement is wired pipe with pressure (and temperature) measurements along the drillstring, giving real-time data of the wellbore (Godhavn, 2010). This technology has been suggested as a tool for pack-off detection and localization in Long and Veeningen (2011). However, how these measurements should be used in an automatic diagnosis system is left open. In Aldred et al. (1998) and Cayeux et al. (2012), a pack-off is detected by monitoring the estimated total friction in the well. In Skalle et al. (2013), pack-offs and other incidents are diagnosed using a knowledge-modeling method.

A challenge with all measurement technology is noise. In this paper the goal is to detect small forming pack-offs at an early stage using simple models and fast detection

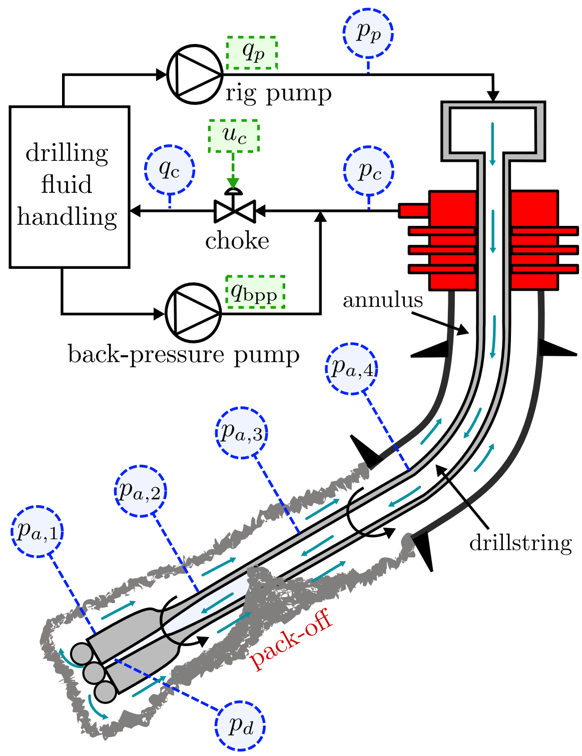


Fig. 1. Drilling process with a forming pack-off. Measurements in blue, actuators in green.

methods, as well as isolating the position, and estimating the magnitude of the incident. This is achieved by applying a multivariate statistical change detection framework on estimated friction parameters and flow rates, giving early diagnosis even with small changes in the estimates.

This paper continues on earlier work on fault diagnosis of downhole incidents in drilling such as *gas influx* from the reservoir, *lost circulation* of drilling fluid to the reservoir, *drillstring washout* (leakage from drillstring to annulus), and *plugging of the drill bit nozzles*, published in Willersrud et al. (2015a,b). There, methods are derived and tested on data from a medium-scale test rig. This paper extends these results by studying how pack-offs, not included in the test rig data, can be diagnosed in simulated data from a full-scale vertical wellbore, using the commercial high-fidelity multi-phase simulator OLGA (Bendiksen et al., 1991).

The paper is organized as follows: In Sec. 2 the model and observer is presented, used to estimate friction parameters and flow rates. Multivariate statistical change detection, and change direction for fault diagnosis are presented in Sec. 3. Simulations of three different pack-offs are presented in Sec. 4, and fault diagnosis of the simulated data is done in Sec. 5. The paper is ended with a conclusion.

## 2. MODELING AND ESTIMATION

The model-based adaptive observer (Willersrud and Imsland, 2013) is presented in this section, which is used to estimate friction parameters and flow rates. First the model itself is presented, then a brief overview of the observer is shown.

### *2.1 Simplified hydraulics model*

The model is a simplified hydraulics model (Kaasa et al., 2012) for managed pressure drilling, given by

$$\frac{dp_p}{dt} = \frac{\beta_d}{V_d}(q_p - q_b), \tag{1a}$$

$$\frac{dp_c}{dt} = \frac{\beta_a}{V_a}\left(q_b + q_{\text{bpp}} - g_c(u_c)\sqrt{|p_c - p_{c,0}|}\right), \tag{1b}$$

$$\frac{dq_b}{dt} = \frac{1}{M}\left(p_p - p_c - F(\theta, q) - (\rho_a - \rho_d) g h_{\text{TVD}}\right), \tag{1c}$$

where $p_p$ is the pump pressure, $p_c$ choke pressure, $q_b$ is the drill bit flow, $q_p$ the pump flow, and $q_{\text{bpp}}$ the back-pressure pump flow, see Fig. 1. Subscript '$d$' denotes drillstring and '$a$' annulus for known volume $V$, bulk modulus $\beta$, and density $\rho$. Parameter $M$ is the integrated density per cross section from pump to choke. Gravitational acceleration is $g$ and $h_{\text{TVD}}$ is the depth of the well. The choke flow is modeled as $q_c = g_c(u_c)\sqrt{|p_c - p_{c,0}|}$, where $g_c(u_c)$ is the choke characteristics as a function of choke opening $u_c \in [0, 100]$, and $p_{c,0}$ is the pressure downstream the choke. The total friction is given by

$$F(\theta, q) = \theta_d f_d(q_b) + \theta_b f_b(q_b) + \theta_a f_a(q_b), \tag{1d}$$

where $f_d$, $f_b$ and $f_a$ are friction terms and $\theta_d$, $\theta_b$, and $\theta_a$ are unknown parameters nominally equal to one, expressing the change in friction in the drillstring, bit, and annulus due to a pack-off. Changes to the parameters due to changed friction is assumed much slower than changes in pressure and flow rates due to operational changes.

The relationship between the pressure measurements, friction, and hydrostatic pressure is given by

$$p_d = p_p - \theta_d f_d(q_b) + \rho_d g h_{\text{TVD}}, \tag{1e}$$

$$p_{a,1} = p_d - \theta_b f_b(q_b), \tag{1f}$$

$$p_{a,1} = p_c + \theta_a f_a(q_b) + \rho_a g h_{\text{TVD}}, \tag{1g}$$

where $p_d$ is the pressure at the bottom of the drillstring, and $p_{a,1}$ the pressure at the bottom of the annulus. If distributed pressure measurements $p_{a,i}$ along the annulus are available, the additional equations give pressure relationships

$$\begin{aligned} p_{a,i} = p_{a,i+1} &+ \theta_{a,i} f_{a,i}(q_b) \\ &+ \rho_a g(h_{a,i} - h_{a,i+1}),\ i \in \{1, \ldots, N_a\}, \end{aligned} \tag{1h}$$

where $\theta_{a,i} f_{a,i}(q_b)$ is the friction of the annular segment between $p_{a,i}$ at depth $h_{a,i}$ and $p_{a,i+1}$ at $h_{a,i+1}$. Note that $f_a = \Sigma_{i=1}^{N_a} f_{a,i}$. The vector of unknown parameters is thus

$$\theta = [\theta_d,\ \theta_b,\ \theta_a,\ \theta_{a,1},\ \ldots,\ \theta_{a,N_a}]^\top. \tag{1i}$$

For typical drilling flow rates, the flow is most commonly turbulent and the friction can be modeled as

$$f_j(q) = k_{j,2} q^2 + k_{j,1}. \tag{2}$$

where $j \in \{d, b, a, a1, a2, a3, a4\}$, and where $k_{j,1}$ and $k_{j,2}$ are constant parameters which can be found using regression of historical pressure and flow rate data.

### *2.2 Adaptive observer*

The states and parameters in (1) are estimated using the adaptive observer in Willersrud and Imsland (2013) with vector of measured states $x = [p_p,\ p_c,\ q_b]^\top$, additional measurements $z = [q_c,\ p_d,\ p_{a,1},\ p_{a,2},\ p_{a,3},\ p_{a,4}]^\top$, inputs $u = [q_p,\ q_{\text{bpp}},\ u_c]^\top$, and unknown parameters given by (1i). It is assumed that bit flow equals pump flow, i.e., $q_b = q_p$, thus ignoring fast drillstring dynamics. The observer is given by

$$\dot{\hat{x}} = \alpha(x, u) + \beta(x)\hat{\theta} - K_x(\hat{x} - x), \tag{3a}$$

$$\dot{\hat{\theta}} = -\Gamma \beta^\top(x)(\hat{x} - x) - \Lambda \lambda^\top(x)(\hat{z} - z), \tag{3b}$$

$$\hat{z} = \eta(x, z, u) + \lambda(x)\hat{\theta}, \tag{3c}$$

where $K_x, \Lambda, \Gamma > 0$ are tuning matrices, and with $\dot{\theta} = 0$. The observer matrices for system (1) are given by

$$\alpha(x, u) = \begin{bmatrix} \frac{\beta_d}{V_d}(u_1 - x_3) \\ \frac{\beta_a}{V_a}(x_3 + u_2) \\ \frac{1}{M}(x_1 - x_2 - (\rho_a - \rho_d) g h_{\text{TVD}}) \end{bmatrix}, \tag{4a}$$

$$\beta(x) = \frac{1}{M}\begin{bmatrix} 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \ldots & 0 \\ -f_d(x_3) & -f_b(x_3) & -f_a(x_3) & 0 & 0 \end{bmatrix}, \tag{4b}$$

$$\begin{aligned} \lambda(x) = \text{diag}\{-f_d(x_3),\ -f_b(x_3),\ f_a(x_3), \\ f_{a,1}(x_3), \ldots,\ f_{a,4}(x_3)\}, \end{aligned} \tag{4c}$$

$$\begin{aligned} \eta(x, z, u) = \Big[ -\frac{\beta_a}{V_a} g_c(u_c)\sqrt{|x_2 - p_{c,0}|},\ x_1 + \rho_d g h_{\text{TVD}}, \\ z_2,\ x_2 + \rho_a g h_{\text{TVD}},\ z_4 + \rho_a g(h_{a,1} - h_{a,2}), \\ \ldots,\ x_2 + \rho_a g h_{a,N_a}\Big]^\top. \end{aligned} \tag{4d}$$

## 3. FAULT DIAGNOSIS

The fault diagnosis method from Willersrud et al. (2015a,b) is presented in this section. Changes to the estimated parameters are detected using multiviariate statistical change detection, and fault isolation is achieved by determining the change direction of the mean of the estimates. The section ends with an overview of the method.

### *3.1 Statistical change detection*

Fault diagnosis is done by detecting changes to estimated states and parameters. This can either be done by detecting changes to each signal independently, or by using a multivariate detection method considering a set of signals jointly. Change detection of data from a medium-scaled drilling test setup, using the same model as in this paper, showed superior results using a multivariate method in Willersrud et al. (2015a). Since the parameter values after change is unknown, a multivariate *generalized likelihood ratio test* (GLRT) is applied to detect and localize a pack-off.

The detection problem is to detect a change in a signal $x(k) \in \mathbb{R}^{N_x}$ of sample size $N$ with probability density function $f(x;\Pi)$ and statistical parameters $\Pi$, by the two hypotheses $\mathcal{H}_0$ (fault-free) and $\mathcal{H}_1$ (fault). This can be done by using a log-likelihood decision function (Kay, 1998),

$$g(k) = \ln \frac{f(X;\Pi_1)}{f(X;\Pi_0)}, \tag{5}$$

where $X = [x(0), \ \ldots, \ x(N)]$, an where $\Pi_0$ are the statistical parameters at $\mathcal{H}_0$, and $\Pi_1$ at $\mathcal{H}_1$.

The two hypotheses are distinguished by using a threshold $h$ of $g(k)$,

$$\begin{aligned} \text{accept } \mathcal{H}_0: &\ \ g(k) \le h, \\ \text{accept } \mathcal{H}_1: &\ \ g(k) > h. \end{aligned} \tag{6}$$

Consider a vector signal with Gaussian noise $x(k) \sim \mathcal{N}(\mu, S)$, with constant covariance matrix $S$ and change in mean $\mu$ from $\mu_0$ at $\mathcal{H}_0$ to unknown $\mu_1$ at $\mathcal{H}_1$. Furthermore, let the noise of signals $x(k)$ be independent and identically distributed (IID). Then the decision function (5) can be written as

$$g(k) = \sum_{i=k-N+1}^{k} (\hat{\mu}_1 - \mu_0)^\top S^{-1} \left( x(i) - \frac{1}{2}(\hat{\mu}_1 + \mu_0) \right), \tag{7}$$

(see, e.g., Basseville and Nikiforov (1993); Blanke et al. (2006)), where

$$\hat{\mu}_1 = \frac{1}{N} \sum_{i=k-N+1}^{k} x(i) \tag{8}$$

is the maximum likelihood estimate of the mean after change. A moving window $M < N$ of the data is used to detect changes within the window.

### *3.2 Fault isolation and estimation*

Changes to different parameters due to different incident types is discussed in Willersrud et al. (2015b) including lost circulation, drillstring washout, gas influx, bit nozzle plugging, and pack-off. To test isolation of a pack-off, tests for all these different scenarios are included. Let $\Delta\hat{q} := \hat{q}_c - \hat{q}_p$ be the change in estimated flow out and in of the well. Changes to estimated parameters and flow rates due to different incidents are listed in Tab. 1. Note that even though only $\hat{\theta}_a$ is changing during a pack-off, all the listed estimated signals need to be checked in order to isolate the pack-off.

Table 1. Change of estimates for different incidents with increasing (+), decreasing (−), and unchanged (0) estimates.

| | $\hat{\theta}_d$ | $\hat{\theta}_b$ | $\hat{\theta}_a$ | $\Delta\hat{q}$ |
|---|---|---|---|---|
| Lost circulation | 0 | 0 | − | − |
| Drillstring washout | − | − | − | 0 |
| Gas influx | 0 | 0 | + | + |
| Bit nozzle plugging | 0 | + | 0 | 0 |
| Pack-off | 0 | 0 | + | 0 |

The change directions for the different incident types can be written as column vectors of

$$\Upsilon_D = \begin{bmatrix} 0 & -1 & 0 & 0 & 0 \\ 0 & -1 & 0 & 1 & 0 \\ -1 & -1 & 1 & 0 & 1 \\ -1 & 0 & 1 & 0 & 0 \end{bmatrix}, \tag{9}$$

where each column represents the scaled change direction of

$$\Theta_D := \left[\hat{\theta}_d, \, \hat{\theta}_b, \, \hat{\theta}_a, \, \Delta\hat{q}\right]^\top, \tag{10}$$

for each of the incidents lost circulation, drillstring washout, gas influx, bit nozzle plugging, and pack-off, respectively. Let $\mu_0^D$ be the mean of the nominal $\Theta_D$, and $\hat{\mu}_1^D$ the estimate (8) of $\Theta_D$ after a change. Defining $D_i := \Upsilon_{D,i}/||\Upsilon_{D,i}||$, the fault can be isolated (Willersrud et al., 2015b), finding

$$i_D^* = \arg\max_i \frac{D_i^\top (\hat{\mu}_1^D - \mu_0^D)}{D_i^\top D_i} \tag{11}$$

of the possible fault indices $i_D \in \mathbb{N}_{N_f} := \{i \in \mathbb{N} : 1 \le i \le N_f\}$, where in this paper, $N_f = 5$. Similarly, (11) can be used to find the position of the fault, once the type is isolated. For a pack-off, possible change directions are the column vectors of

$$\Upsilon_I = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} \tag{12}$$

for the estimated annulus parameters

$$\Theta_I := \left[\hat{\theta}_{a,1}, \, \hat{\theta}_{a,2}, \, \hat{\theta}_{a,3}, \, \hat{\theta}_{a,4}\right]^\top, \tag{13}$$

since a pack-off will be seen as an increase in friction between two pressure sensors $p_{a,i}$ and $p_{a,i+1}$, thus increasing $\hat{\theta}_{a,i}$.

### *3.3 Overview of fault diagnosis method*

The fault diagnosis method used in this paper and presented in this section consists of estimating states and parameters, detecting changes to them, and determining in which direction they are changing. The steps in the method are shown in Fig. 2 and can be summarized as follows:

(1) Friction parameters and flow rates are estimated using the adaptive observer (3).
(2) Changes to the subset of estimated states and parameters $\Theta_D$ given by (10) is detected using the GLRT decision function (7).
(3) The type of fault is isolated using (11), with possible change directions of $\Theta_D$ as columns in (9).
(4) The position is located with (11), with possible change directions of $\Theta_I$ as column vectors in (12).

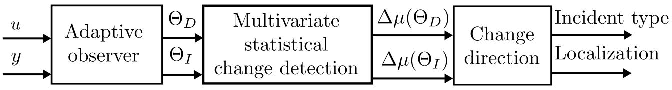


Fig. 2. Fault diagnosis overview.

## 4. PACK-OFF SIMULATION IN OLGA

OLGA is a high-fidelity dynamic multiphase flow simulator, which is used to simulate a series of pack-offs in a vertical wellbore of 2530 meters. The well is modeled as an annulus with typical radii, including the so-called bottom hole assembly with narrower flow paths, as well as several restrictions representing joints of the drillstring. Water is used as drilling fluid, with a circulation rate of 1000 L/min, a typical flow rate for drilling operation. The model includes an MPD choke, while the back-pressure pump is omitted. A vertical well is chosen for simplicity, but a deviated well would give the same results. The friction coefficients $k_{j,1}$, $k_{j,2}$ for $f_j(q_b)$, $j \in \{d, b, a, a1, a2, a3, a4\}$ are found using regression of the pressure drop adjusted for hydrostatic pressure during a test where the flow rate is varied in the range 300-1100 L/min.

Pack-offs are local build ups of solids in the annulus, partly or fully blocking the flow. This behavior is similar to a choke restriction, and pack-offs are therefore simulated in OLGA using chokes at three different positions in the well. The chokes are gradually opened and then closed with varying magnitude between each one. There are four pressure sensors in the annulus representing a wired drill pipe, in addition to a sensor measuring the choke pressure at the top, see Fig. 1. The sensors are located at depth $h_a = [2530,\ 1980,\ 1230,\ 330]^\top$. The first pack-off choke ($u_{po,1}$) is located between sensor $p_{a,1}$ and $p_{a,2}$, the second ($u_{po,2}$) between $p_{a,2}$ and $p_{a,3}$, and the third ($u_{po,3}$) between $p_{a,3}$ and $p_{a,4}$. A cause of forming pack-offs is insufficient circulation. Therefore is the flow-rate increased to 1100 L/min after the second pack-off, which would be a probable action taken by the drilling operator if a pack-off was detected. Here, this is done to test the diagnosis method for varying pressure and flow rates.

Gaussian distributed white noise is added to all measurements, with standard deviation $\sigma = 0.001\mu_0$ of each measurement, where $\mu_0$ is the mean at the fault-free case $\mathcal{H}_0$, although a larger variance of the signals could easily been used. This fault free case is a time interval known to be without any incidents. In a real case, this would typically be during drilling with constant pressures and flow rates, where the operator has full overview of the situation. In the simulation this interval is between 5 and 40 minutes drilling time.

States and parameters are estimated using the adaptive observer (3) with tuning matrices $K_x = \text{diag}(1, 1, 1)$ and $\Gamma = \Lambda = 5 \times 10^{-5} \times \text{diag}(1, 1, 1, 1, 1, 1, 1)$. Simulations and state estimation are shown in Fig. 3, illustrating measured and estimated pump pressure, choke pressure, pump flow and bit flow. The bottom panel shows openings of the three different valves. This affects the pump pressure, since the total friction in the well increases. All three pack-offs are visible in $p_p$, but may be difficult to distinguish from changes due to varying operating conditions.

The resulting parameter estimation is plotted in Fig. 4, showing parameters used in $\Theta_D$ for incident type isolation in the upper panel, and $\Theta_I$ used for localization in the lower. In the upper panel, only $\hat{\theta}_a$ is changing due to a pack-off, in accordance with Tab. 1 and (9). Furthermore, the need for statistical change detection is apparent, since changes are small. In the lower panel, pack-offs at different positions are affecting the estimated annular parameters differently, which is used in incident localization. Note that also here, statistical change detection is needed, in particular to detect changes in $\hat{\theta}_{a,3}$.

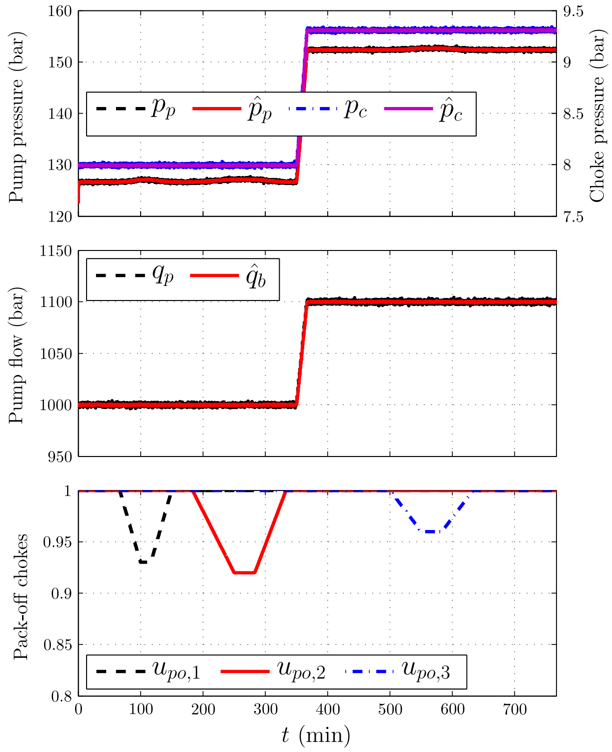


Fig. 3. Pressure and flow estimation, and valve openings simulating pack-offs.

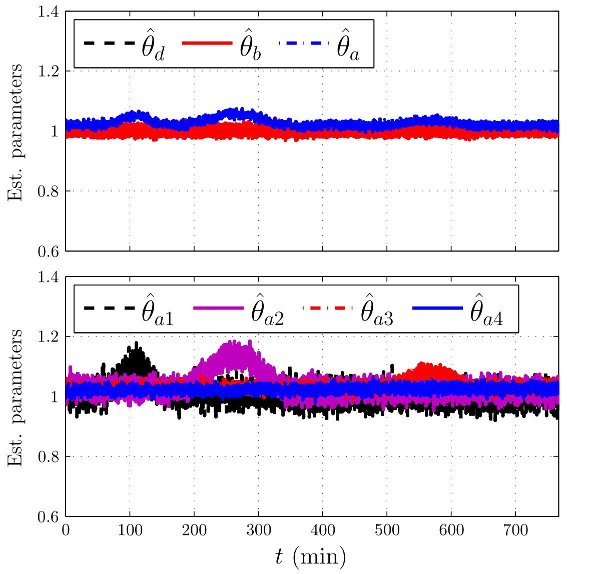


Fig. 4. Estimation of friction parameters.

## 5. PACK-OFF DIAGNOSIS

Fault diagnosis of pack-offs in simulated OLGA data, shown in Figs. 3 and 4, is done according to the steps presented in Sec. 3.3. Diagnosis results are shown and discussed in this section.

### 5.1 Threshold

Theoretical thresholds for the GLRT (5) is given in Kay (1998), where as $N \to \infty$, the test statistic has the asymptotic probability density function (PDF) $\chi_r^2$ under $\mathcal{H}_0$ and $\chi_r^2(\lambda)$ under $\mathcal{H}_1$, where $r$ is the number of statistical parameters that are changing and $\lambda$ is a non-central parameter. This asymptotic distribution can be used to derive a threshold $h$ as a function of the probability of false alarms $P_{\text{FA}}$. However, this property holds asymptotically, whereas in this case a limited window $M$ is used. Furthermore, the asymptotic PDF of the GLRT assumes IID data. The estimated parameters and flow rates from observer (3) are clearly not IID, since the observer acts as a filter of current and previous measurements. Such discrepancy between the asymptotic IID result and a real distribution was also shown to exist in position mooring diagnosis in Blanke et al. (2012).

A Weibull probability plot of $g(k)$ for $\Theta_D$ at $\mathcal{H}_0$ is shown in Fig. 5 together with a $\chi_r^2$-distribution with $r = 4$ (change in mean of $\Theta_D \in \mathbb{R}^4$), and a fitted Weibull distribution. This plot shows that the test statistic better fits a Weibull distribution, which therefore will be used to determine thresholds. Fitting GLRT statistics to distrubutions other than the $\chi^2$-distribution, such as the Weibull and lognormal distributions, was done in Galeazzi et al. (2013) and Hansen and Blanke (2014).

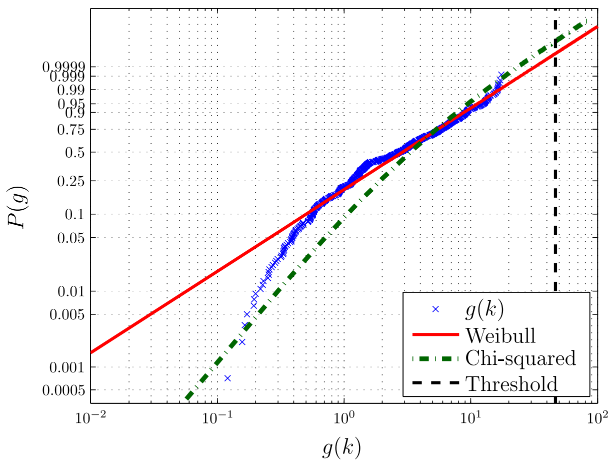


Fig. 5. Weibull probability plot of $g(k;\Theta_D)$ at $\mathcal{H}_0$ for Weibull and $\chi_4^2$-distribution.

Table 2. Threshold values.

| Threshold | Weibull | $\chi_4^2$ |
|---|---|---|
| $h_D$ | 46.6 | 33.4 |
| $h_I$ | 83.7 | 33.4 |

Let $Q(x; \alpha, \beta)$ be the inverse cumulative distribution of the Weibull distribution with statistical parameters $\alpha$, $\beta$. Then the threshold for a desired $P_{\text{FA}}$ is given by

$$h = Q(1 - P_{FA}; \mathcal{H}_0, \alpha_0, \beta_0) = \beta_0 \left(-\ln(P_{FA})\right)^{1/\alpha_0}, \quad (14)$$

where $\alpha_0$ and $\beta_0$ are the statistical parameters fitted to $g(k)$ of data $\Theta_D$ and $\Theta_I$ under $\mathcal{H}_0$. The thresholds for $g(k;\Theta_D)$ and $g(k;\Theta_I)$ with $P_{\text{FA}} = 10^{-6}$ are given in Tab. 2 for the real (Weibull) and theoretical ($\chi^2$) case.

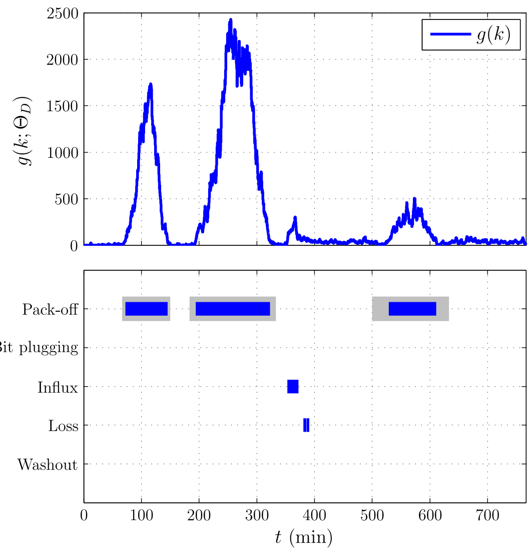


Fig. 6. Pack-off detection and isolation. Actual pack-offs are shown in grey.

### 5.2 Pack-off detection and isolation

The fault diagnosis method is applied on the estimated parameters and states. Fault type isolation is shown in Fig. 6, where the upper panel shows the value of $g(k)$ of $\Theta_D$ using a window length $M = 100$, the lower panel shows incident type isolation. In addition, there is a requirement of 100 consecutive samples (10 s) of $g(k)$ above threshold before an alarm is set. This figure clearly shows that all three pack-offs are correctly detected and isolated, with some brief false alarms during change of flow rate, which can be ignored since this change is known. It is assumed that the estimated parameters and states are IID, while they actually are slightly correlated with previous samples. However, assuming IID signals and using (7) is shown here to give sufficient detection. If no statistical change detection method was used, and a threshold of the unfiltered $\hat{\theta}_a$ was to be applied directly, detection would be uncertain, and selecting a proper threshold for $\hat{\theta}_{a,3}$ seen in Fig. 4 would be difficult if not impossible.

Position localization is shown in Fig. 7, showing $g(k)$ for change detection of $\Theta_I$ in the upper panel and localization in the lower. Also here, the fault diagnosis method successfully manages to detect the change in parameters and localize the position of the pack-off. It would be possible to estimate the location of the pack-off with some uncertainty, but that would require high accuracy modeling of the well geometry. The method in this paper focuses on simple modeling, with position localization limited a segment between two pressure sensors.

Pack-offs are typically building up quite slowly in a real scenario. However, due to limiting simulation times, the simulated pack-offs are occurring quite fast. The strength of the diagnosis method is that both abrupt (fast) and incipient (slowly varying) incidents can be diagnosed.

### 5.3 Pack-off magnitude estimation

The frictional pressure drop due to a pack-off is possible to estimate once the fault is detected and isolated. A pack-off will increase the friction in the annulus with the amount $F_{po}$. The total estimated annulus friction is given by

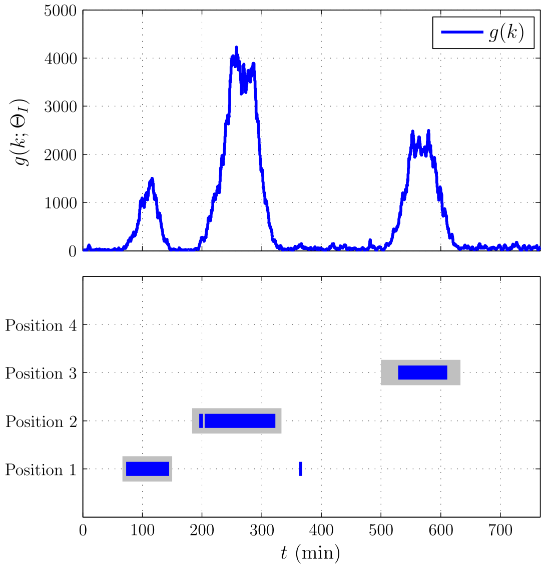


Fig. 7. Pack-off localization. Actual location shown in grey.

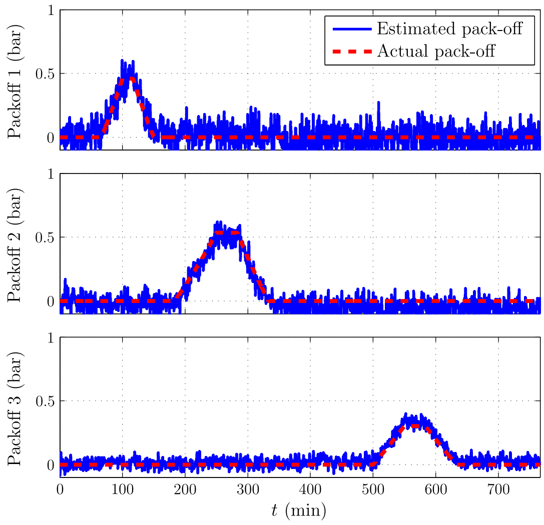


Fig. 8. Pack-off magnitude estimation.

$\hat{F}_a = \hat{F}_{po} + \hat{F}_{a,0} = (\hat{\theta}_a - \mu_{a,0})\hat{q}_b^2 + \mu_{a,0}\hat{q}_b^2$, where $\hat{F}_{a,0}$ is the annulus friction without pack-offs and $\mu_{a,0} = E(\hat{\theta}_a; \mathcal{H}_0)$ is the mean of the annulus parameter at $\mathcal{H}_0$. The pack-off friction magnitude can thus be estimated as

$$\hat{F}_{po} = (\hat{\theta}_a - \mu_{a,0})\hat{q}_b^2. \quad (15)$$

The low-pass filtered estimated pack-off magnitudes are shown in blue in Fig. 8, with actual pressure drop from OLGA simulations without noise shown in red. The plots show accurate magnitude estimation of all three pack-offs. By combining parameter estimation with a change detection method, fault diagnosis is hence possible, as well as fault magnitude estimation. This is one of the strengths of using estimation of physical parameters, or lumped physical parameters, as a basis for fault diagnosis.

## 6. CONCLUSION

Pack-off in drilling is a severe event which can lead to costly downtime. Simulations in OLGA are used to test a fault diagnosis method for pack-off detection, isolation, localization, and magnitude estimation. Three pack-offs at different positions and sizes are successfully diagnosed with early detection and low false alarm rates, even with noticeable noise in the measurements. A multivariate generalized likelihood ratio test is applied to detect changes in a set of estimated friction parameters and flow rates affected by noise. By determining the direction of change of a subset of the signals, the type of fault and location is correctly isolated as pack-offs at different positions, and at an early stage with specified probability of false alarms. Once the pack-off is diagnosed, its magnitude is correctly estimated from the estimated friction parameters.

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