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Erosion state estimation for subsea choke valves considering valve openings

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Choke valves are extensively used in the offshore oil industry, where they regulate the flow of hydrocarbon fluids from the oil wells and reduce the wellhead pressure. They are subject to continuous erosion that results from the impingement of solid particles in the hydrocarbon fluids. Since maintenance and inspections are costly for subsea choke valves due to the reduced accessibility, it is crucial to evaluate the erosion state of chokes accurately.
One health indicator of erosion is the difference between the theoretical and estimated valve flow coefficients (Cv), a relative measure of the efficiency at allowing fluid flow. Traditionally, the Cv deviation is fit by a Gamma process. We show why this approach is unrealistic in practice before proposing a model that uses the historical valve openings and process parameters to calibrate raw Cv measurements. This allows us to estimate the erosion rate at different valve openings and reveal the "true" erosion state, which differs from the raw Cv. The least-squares method is used to estimate the baseline shape of the Cv deviation curve. We apply our method to Equinor's choke valve erosion data, showing that the new method, compared to traditional ones, gives a more accurate estimation of the erosion state which can then be used to provide decision support for production and maintenance managers.

Keywords: PHM, choke valve erosion, degradation, parameter estimation.

1. An introduction to the function and erosion of choke valves

Located in a harsh environment, subsea systems are prone to degradation and failures. Due to the inaccessibility, field inspections and maintenance on subsea systems are generally complex, expensive, and cannot be carried out without a certain delay. Thus, monitoring and estimating the system's health state and predicting the systems' remaining useful lifetime (RUL) bears a recognized value in industrial facilities' safety and economic aspects.

Production chokes are designed to take the brunt of the pressure off the line components, increasing their life and yielding significant benefits. By restricting the flow to a small opening or orifice, a choke valve reduces the well pressure, controls production rate, creating downstream or back pressure. They stand out as the components in oli & gas production systems that are most susceptible to erosion DNVGL-RP-O501 (2015), due to the potential for high flow velocities created by the pressure let-down across the choke. Because of sand production, drilling, and hydraulic fracking, the abrasive well stream often consists of a mix between oil, gas, water, sand, and other particles such as calcite and proppants, which aggravates the erosion.

Numerous researches investigated wear and erosion from a material or flow perspective. For example, Haugen et al. (1995) examined the sand erosion of wear-resistant materials; Wheeler et al. (2006) addressed the application of diamond to enhance choke valve's lifetime; Wood (2006) investigated the erosion–corrosion interactions and their effect on marine and offshore materials; Gharaibah and Zhang (2016) used CFD to build erosion prediction models for piping elements. Most of the work is helpful for the design phase but can hardly be applied in the operation phase for online condition monitoring of the choke, where we measure the performance indicator in real-time and raise the alarm if an anomaly is detected.

1.1. *Health indicator*

Valve Flow Coefficient (Cv) is a valve's capacity for a liquid or gas to flow through it. It is technically defined as "the volume of water at 60° Fahrenheit (in US gallons) that will flow through a valve per minute with a pressure drop of 1 psi pound per square inch across the valve." As a valve opens, the Cv increases until the valve is fully open, reaching its highest possible value. An example of theoretical Cv is shown in Figure 1.

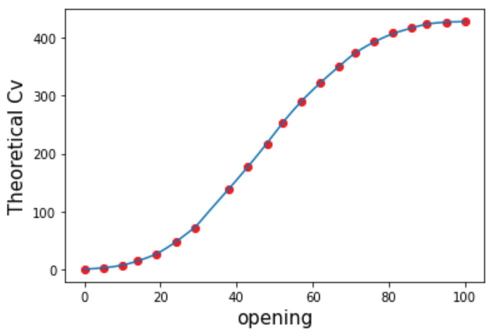

Fig. 1.: Theoretical Cv of a production choke. X-axis is the relative valve opening in percentage.

One health indicator of the erosion process could be the difference between the theoretical and estimated valve flow coefficients (Cv) DNVGL-RP-O501 (2015). For example, for multistage/labyrinth cage with interval plug choke, Cv deviation can reveal the level of damage since the labyrinths wear gradually. It has also been documented in Nystad et al. (2010) the use of Cv deviation to evaluate the health state of disc-type chokes. According to IOHN report (2012), when the deviation finally passes a predefined threshold, the choke should be inspected. Efforts have been made to obtain a more accurate estimation of Cv deviation using valve opening and process parameters Baraldi et al. (2011); Paggiaro et al. (2013).

1.2. *Limitations of existing approaches*

Traditionally, the erosion of a choke valve is considered a monotonic process: as the erosion becomes more and more severe, the pass area inside the choke valve grows due to material loss, allowing the fluid to pass more easily, and the actual Cv continuously rises. This led to a straightforward RUL estimation method: the Cv deviation is modeled by a Gamma process, a continuous, monotonically increasing jump process. When the Cv measurements are non-monotone, it is considered contaminated by Gaussian noise, and the whole sequence is filtered to be non-decreasing so that a Gamma process can fit the data Nystad et al. (2010). The distribution of RUL is then calculated based on the first passage time of the Gamma process with respect to a predefined failure threshold Zhang et al. (2016). Some also considered the filtering techniques for Gamma processes perturbed by noise Liu et al. (2022). However, the assumption that Cv deviation is monotonically increasing could be unrealistic since sand production can block the passages inside a choke valve, leading to temporal reduction of Cv. Besides, influence of choke opening on the Cv measurements has not been discussed.

1.3. *Contribution and organization*

We propose in this paper a model that uses historical valve openings and process parameters to calibrate the raw Cv measurement. Based on least squares, it computes the initial shape of the Cv deviation curve and estimates the erosion rate at different valve openings. As a result, it reveals the "true" erosion state (referred to in this paper as "adjusted Cv deviation") which can differ a lot from the raw Cv deviation.

The paper is organized as follows. In section 2, we highlight the importance of considering valve opening when evaluating the degradation of a choke valve. Section 3 presents the principle and formulations of our new model. Case studies on real choke erosion data are provided in section 4. Concluding remarks are given in section 5.

2. Valve opening and Cv measurements

Using the Cv deviation as a degradation indicator requires a careful definition of the theoretical Cv, which itself depends on the valve opening, or travel. According to Control Valve Handbook (2019), travel is defined as "the movement of the closure member from the closed position to an intermediate or rated full-open position". We use the word "opening" to denote the travel in percentage, i.e., 0% for fully closed, and 100% for fully open. Since previous work on using Cv data to monitor the choke valve condition rarely addressed the influence of valve opening, we present in this section why and how valve opening should be taken into account.

2.1. *Observed Cv and theoretical Cv*

Let $\boldsymbol{t} = \{t_0, t_1...t_n\}$ be the observation times (days). $\boldsymbol{t}$ may or may not be equally-spaced, but is usually discrete and belongs to the set of integers. Let $\boldsymbol{h} = \{h_0, h_1...h_n\}$ be the openings at time $t_0, t_1....$ And let $\boldsymbol{x} = \{x_0, x_1...x_n\}$ be the corresponding observed Cv deviations:

$$\forall i \in 0...n, x_i = Cv^{obs}(t_i, h_i) - Cv^{theo}(h_i). \quad (1)$$

where $Cv^{theo}(h_i)$, the theoretical Cv at opening h_i, is independent of time and can be found in technical documents. The observed Cv at time t_i, $Cv^{obs}(t_i, h_i)$, depends on both time and valve opening. If at time $t = t_0$ the valve is good as new, then the initial degradation state at t_0 is 0 for any openings. In reality, the Cv record and operational history are often incomplete, and the valve is already eroded to some extent at the beginning of the observation.

The valve's performance degrades with time and usage, and the Cv curve will evolve along the time axis, slowly "drifting away" from the theoretical values. The actual Cv deviation, denoted as $y(t, h)$, is the erosion ground truth. Thus, the observed Cv deviation $\boldsymbol{x}$ is just a discrete sampling of y, at instants $t_0, t_1, t_2...$ and at openings $h_0, h_1, h_2....$ Our goal is to infer y from $\boldsymbol{x}$ and $\boldsymbol{h}$.

2.2. *Initial Cv deviation curve*

The initial Cv deviation curve (ICDC) is defined as the Cv deviation curve (as a function of valve opening) at the very beginning of the observation. The shape of ICDC can be visualized by plotting $\boldsymbol{x}$ against opening and time as in Figure 2.

Figure 2 emphasizes the movement from one datum to the next: instead of plotting data pairs (h_j, x_j), we draw colored vectors from (h_{j-1}, x_{j-1}) to (h_j, x_j). In the early phase, the

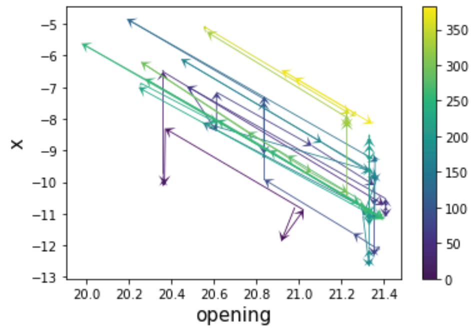

Fig. 2.: Evolution of Cv deviation curve of a production choke during its 350 working days. At any instant, the Cv deviation (y-axis on the left) is a function of opening (x-axis), and moves up and down with time (y-axis on the right).

data points are linked by dark purple arrows, then rise and fall until the last day, where the arrows become light yellow. Most arrows share the same slope except for those vertical displacements. Thus, one can make an intuitive assumption that the ICDC has a straight-line shape and moves up and down as a whole due to external shocks.

From Figure 2, we notice that the true erosion can be masked by the changes in the valve opening: when the opening is switched to a small value, the Cv deviation becomes larger, and vice versa. This is not related to erosion and is referred to as "observation bias". Also, the Cv can decrease due to clogging, which affects the internal geometry of the choke. Figure 2 shows that the erosion was decreasing from around day 150 (dark green) to day 250 (light green) continuously. One possible explanation is massive sand production blocking the pass area inside the choke, leading to a reduced capacity to allow the fluid to pass. Such behaviour prevents the use of any monotonic stochastic process, such as Gamma or IG process, to describe the degradation process.

3. New model for erosion state estimation

Let $\{f_0(h), f_1(h)...f_n(h)\}$ be the sequence of functions representing Cv deviation curves at time $t_0, t_1...t_n$. $f_0(h)$ is the ICDC. Our goal is to estimate $f_j(h)$ based on $\boldsymbol{t}$, $\boldsymbol{h}$ and $\boldsymbol{x}$.

The basic assumption is that the increment in the raw Cv deviation, $x_j - x_{j-1}$, can be decomposed as

- a shift along the Cv deviation curve (observation bias)
- a local erosion at opening h_{j+1}
- a vertical displacement δ_j representing global erosion caused by external shocks

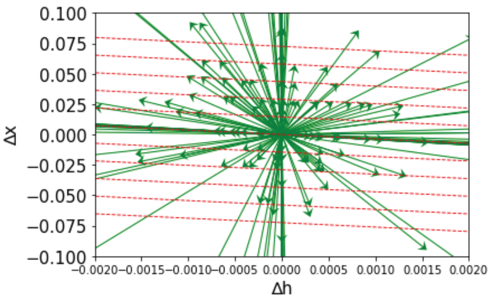

Fig. 3.: Δx versus Δh. Red grid represents presumably the Cv deviation curve, which is here a straight line. The observed Cv deviation increment (green arrow) can be decomposed as a vertical movement (erosion) and a shift along the red grid (observation bias).

The above decomposition can be justified by Figure 3 where all the arrows in Figure 2 are shifted to origin. When Δh is close to 0, we notice that most arrowheads sit on a red grid composed of parallel straight lines with a slope of -3.65. This is the supposed Cv deviation curve, which causes the observation bias.

As the first measurement (h_0, x_0) is traversed by f_0, it is straightforward that

$$f_0(h) = x_0 + f(h) - f(h_0) \tag{2}$$

where $f(h)$ determines the shape of Cv deviation curves. E.g., $f(h) = \beta h$ is a straight line.

Let $g(h)$ be the daily Cv deviation growth at opening h, independent of the historical process parameters and openings. $g(h)$ is introduced because the Cv deviation rates at different openings are sometimes not the same: the Cv tends to deviate more at smaller openings than at larger openings. Let $\Delta t_j = t_j - t_{j-1}$ be the time gap between two consecutive observations. $\Delta t_j g(h)$ represents the local Cv deviation growth at h. The sequence $\{f_0(h), f_1(h)...f_n(h)\}$ are governed by the recursive equation system:

$$\begin{cases} f_j(h) = f_{j-1}(h) + \delta_j + \Delta t_j g(h) \\ f_j(h_j) = x_j \end{cases} \tag{3}$$

Let $\Delta f_j = f(h_j) - f(h_{j-1})$. The solution of Eq.(3) (in non-recursive form) is given below.

$$\begin{cases} f_j(h) = x_j + f(h) - f(h_j) + t_j(g(h) - g(h_j)) \\ \delta_j = \Delta x_j - \Delta f_j - (t_j g(h_j) - t_{j-1} g(h_{j-1})) \end{cases} \tag{4}$$

The vector of shocks, $\boldsymbol{\delta} = [\delta_1, \delta_2...\delta_n]^T$ corresponds to the vertical displacements of the Cv deviation curve that cannot be explained by the local erosion growth $g(h)$ and the initial shape $f(h)$. It can be treated as noise if there is no prior knowledge about $\boldsymbol{\delta}$. To explain the observations as much as possible by f and g, the squared sum of $\boldsymbol{\delta}$ is minimized. Suppose that f and g are equipped with parameters $\boldsymbol{\beta}$ and $\boldsymbol{\gamma}$. The least-squares estimates of $\boldsymbol{\beta}$ and $\boldsymbol{\gamma}$ are:

$$\boldsymbol{\beta}^*, \boldsymbol{\gamma}^* = \arg\min_{\boldsymbol{\beta},\boldsymbol{\gamma}} ||\boldsymbol{\delta}||_2 = \arg\min_{\boldsymbol{\beta},\boldsymbol{\gamma}} \boldsymbol{\delta}^T \boldsymbol{\delta} \tag{5}$$

3.1. *f is a polynomial*

In the special case where f and g are polynomials, the estimates have closed-form solution. Let $f(h) = \sum_{i=1}^{p} \beta_i h^i$ and $g(h) = \sum_{i=0}^{q} \gamma_i h^i$. Then, Eq.(4) can be written as

$$\boldsymbol{\delta} = \boldsymbol{\Delta x} - \boldsymbol{U\theta} \tag{6}$$

where $\boldsymbol{\theta} = [\beta_1, ...\beta_p, \gamma_0...\gamma_q]^T$ is the concatenated vector of parameters. $\boldsymbol{U} = [\boldsymbol{U_\beta}, \boldsymbol{U_\gamma}]$, where $\boldsymbol{U_\beta}$ is a $n \times p$ matrix with $\boldsymbol{U_\beta}(i,j) = h_i^j - h_{i-1}^j$, and $\boldsymbol{U_\gamma}$ is a $n \times (q+1)$ matrix with $\boldsymbol{U_\gamma}(i,j) = t_i h_i^{j-1} - t_{i-1} h_{i-1}^{j-1}$. The closed-form solution for $\boldsymbol{\theta}^*$ is therefore:

$$\boldsymbol{\theta}^* = (\boldsymbol{U}^T \boldsymbol{U})^{-1} \boldsymbol{U}^T \boldsymbol{\Delta x} \tag{7}$$

3.2. *f is piecewise linear*

Another possible choice for $f(h)$ is a piecewise linear model. In some field data, we observe that there exists a breaking point (BP) in the valve openings: the Cv deviations before and after the BP are significantly different, e.g., with different slopes. In this case, $f(h)$ can be described by a continuous piecewise linear function.

When there is only one BP, $f(h)$ is equipped with 3 parameters as:

$$f(h) = \begin{cases} \beta_1 h & \text{if } h \leq b \\ \beta_2 h + (\beta_1 - \beta_2) b & \text{otherwise} \end{cases} \tag{8}$$

where b is the BP, and β_1, β_2 are the slopes before and after b. The term $(\beta_1 - \beta_2)b$ ensures that $f(h)$ is continuous at b. Parameter estimation can be achieved by Eq.(5), but no closed-form solution exists because the least-squares regression is not linear. When there are p breaking points, say $\boldsymbol{b} = b_1, b_2...b_p$, $f(h)$ has $p+1$ segments. Let $b_0 = 0$ and $b_{p+1} = 100\%$, then,

$$f(h) = \sum_{j=1}^{p+1} \Bigg(\big(\beta_j h + \sum_{i=1}^{j-1} (\beta_i - \beta_{i+1}) b_i \big) \times \mathbb{1}(b_{j-1} < h \leq b_j) \Bigg) \tag{9}$$

When $\boldsymbol{b}$ is unknown the regression is non linear. However, if prior knowledge and experts' opinions are available for identifying the break points, the parameters to be estimated reduce to $\boldsymbol{\beta} = \beta_1, \beta_2 ... \beta_{p+1}$, and closed-form solution can be derived. It suffices to redefine the matrix $\boldsymbol{U_\beta}$ in $\boldsymbol{U}$ in Eq.(6). Here, $\boldsymbol{U_\beta}$ is a $n \times (p+1)$ matrix whose (i,j) entry is given by:

$$\begin{aligned} \boldsymbol{U_\beta}(i,j) &= (h_i - b_{j-1}) \mathbb{1}(b_{j-1} < h_i \leq b_j) \\ &+ (b_j - b_{j-1}) \mathbb{1}(h_i > b_j) \\ &- (h_{i-1} - b_{j-1}) \mathbb{1}(b_{j-1} < h_{i-1} \leq b_j) \\ &- (b_j - b_{j-1}) \mathbb{1}(h_{i-1} > b_j) \end{aligned} \tag{10}$$

A brief proof for Eq.(10) is given below. Let $\boldsymbol{\beta}$ be a column vector. Let $\boldsymbol{B}_h$ be a $(p+1) \times (p+1)$ upper triangular matrix with $\boldsymbol{B}_h(i,i) = h - b_{i-1}$, $\boldsymbol{B}_h(i,j) = b_i - b_{i-1}$ if $j > i$ and 0 otherwise. Let $\boldsymbol{D}_h$ be a column vector of length $p+1$ with $\boldsymbol{D}_h(i) = \mathbb{1}(b_{i-1} < h \leq b_i)$. Therefore,

$$f(h) = (\boldsymbol{B}_h \boldsymbol{D}_h)^T \boldsymbol{\beta} \tag{11}$$

The i-th row of $\boldsymbol{U_\beta}$, when multiplied by $\boldsymbol{\beta}$, equals to $f(h_i) - f(h_{i-1})$. $\boldsymbol{U_\beta}(i,j)$ is therefore the j-th element of $\boldsymbol{B}_{h_i} \boldsymbol{D}_{h_i} - \boldsymbol{B}_{h_{i-1}} \boldsymbol{D}_{h_{i-1}}$.

$$\begin{aligned} \boldsymbol{B}_h \boldsymbol{D}_h(j) &= \boldsymbol{B}_h(j,:) \boldsymbol{D}_h \\ &= \sum_{s=1}^{j-1} 0 \cdot \mathbb{1}(b_{s-1} < h \leq b_s) \\ &+ (h - b_{j-1}) \mathbb{1}(b_{j-1} < h \leq b_j) \\ &+ (b_j - b_{j-1}) \sum_{t=j+1}^{p+1} \mathbb{1}(b_{t-1} < h \leq b_t) \end{aligned} \tag{12}$$

where the first sum is 0 and the last sum is $\mathbb{1}(h > b_j)$, which proves Eq.(10).

3.3. *g depends on process parameters*

Previously, function $g(h)$ gives the daily Cv deviation growth at opening h, independent of historical openings. Nevertheless, field experience suggests that the erosion is more severe when operating at a small opening and is mild at larger openings. E.g., for a plug & cage choke valve, when the cage ports are fully open, the high-velocity jets are perpendicular to the valve axis, and energy is dissipated; otherwise, the jets are directed toward the valve outlet and aggravates its erosion over time.

Valve opening influences the fluid's direction, which determines the particle impact angle. According to the erosion response model in DNVGL-RP-O501 (2015), the material loss is proportional to both the particle impact velocity (which equals approximately the fluid velocity) and $F(\alpha)$, the ductility of the target material with impact angle α. We do not seek to establish a precise relation between α and opening. Instead, we assume the daily Cv growth g at opening h depends on the previous day's opening and flow rate Q. In this scenario, measurement times should be equally spaced: $t_j - t_{j-1} = 1, j = 1, 2, ...$ As such, Eq.(3) becomes:

$$\begin{cases} f_j(h) = f_{j-1}(h) + \delta_j + g(h | Q_{j-1}, h_{j-1}) \\ f_j(h_j) = x_j \end{cases} \tag{13}$$

To simplify the notations, we define $g_{k,j} = g(h_k | Q_j, h_j)$ and $g_{\cdot,j} = g(h | Q_j, h_j)$. The solution of Eq.(13) is given below:

$$\begin{cases} f_j(h) = x_j + f(h) - f(h_j) + \sum_{i=0}^{j-1}(g_{\cdot,i} - g_{n,i}) \\ \delta_j = \Delta x_j - \Delta f_j - \sum_{i=0}^{j-2}(g_{j,i} - g_{j-1,i}) - g_{j,j-1} \end{cases} \tag{14}$$

If the observation times are not equally spaced, we can either complete the missing data by statistical methods or establish the following equations system:

$$\begin{cases} f_j(h) = f_{j-1}(h) + \delta_j + \Delta t_j g(h|Q_{j-1}, h_{j-1}) \\ f_j(h_j) = x_j \end{cases} \tag{15}$$

where $\Delta t_j g(h|Q_{j-1}, h_{j-1})$ represents the degradation growth during t_{j-1} and t_j at opening h, given the latest datum (Q_{j-1}, h_{j-1}) observed on day t_{j-1}. Eq.(15) implicitly assumes that the process parameters (Q_{j-1}, h_{j-1}) remain constant between t_{j-1} and t_j. The corresponding formulas for f and δ are shown respectively by Eq.(16) and (17). Model parameters can then be estimated by Eq.(5).

$$\begin{aligned} f_j(h) &= x_j + f(h) - f(h_j) \\ &\quad + \sum_{i=1}^{j-1} t_i(g_{\cdot,i-1} - g_{\cdot,i} - g_{j,i-1} + g_{j,i}) \\ &\quad + t_j(g_{\cdot,j-1} - g_{j,j-1}) \end{aligned} \tag{16}$$

$$\begin{aligned} \delta_j &= \Delta x_j - \Delta f_j \\ &\quad - \sum_{i=1}^{j-2} t_i(g_{j,i-1} - g_{j,i} - g_{j-1,i-1} + g_{j-1,i}) \\ &\quad - t_{j-1}(g_{j,j-2} - g_{j,j-1} - g_{j-1,j-2}) - t_j g_{j,j-1} \end{aligned} \tag{17}$$

3.4. *Model selection*

The example presented in Figure 2 indicates a relatively simple form for the ICDC. Indeed, to avoid overfitting, f and g should not be too complex. In the extreme case, we can define an f_0 that traverses every datum, but such a model is "static", does not change over time, and cannot describe a choke valve's erosion.

Let $\mathcal{M} = \{M_1, M_2...\}$ be the set of candidate models. The classic cross-validation consists in dividing the data into training set and testing set. However, it does not apply as we are dealing with time series data. Therefore, to evaluate a model's ability to generalize, we use the original data and its subset (r out of n data points) as testing set and training set. The procedure is shown below. In Algorithm 1, N is a large number, typically 500 or 1000; r can be set as 0.75*n.

Algorithm 1 Model selection

1: **for** M in $\mathcal{M}$ **do**
2: **for** i in 1...N **do**
3: Build training set by randomly select r data points
4: Compute optimal parameter $\boldsymbol{\theta}_M^{(i)}$ for the training set with Eq.(5)
5: Compute $\boldsymbol{\delta}_M^{(i)}$ with $\boldsymbol{\theta}_M^{(i)}$ for the entire data set with (Eq.6)
6: **end for**
7: Compute mean error for model M: $\bar{\epsilon}_M = \sum_{i=1}^{N} ||\boldsymbol{\delta}_M^{(i)}||_2/N$
8: **end for**
9: Select M with minimal mean error

4. Case study and discussion

Consider the Cv deviation of a production choke of type CV428. The observation covers 413 days, with 288 data in total. Raw Cv is plotted against opening in Figure 4 and time in 5. Large fluctuations between day 170 and day 300 cannot be explained by our model and deserves a more careful examination by consulting the event log. So here we remove those data.

The evolution of Cv deviation curve is shown in Figure 6. The slope of the arrows appears to be increasing in time: the purple curves at the beginning of observation have a smaller slope than the yellow ones at the end of observation. Two scenarios are most probable: first, ICDC is a straight line, and Cv deviation grows faster at smaller openings than at larger openings; second, ICDC is a parabola that is "flat" at smaller openings and "steep" at larger openings.

We fit a polynomial to f and g, so as to determine the shape of ICDC and the unbalanced erosion rate. Candidate models are polynomials with $p, q \in \{(1,0), (1,1), (1,2), (2,0), (2,1), (2,2)\}$.

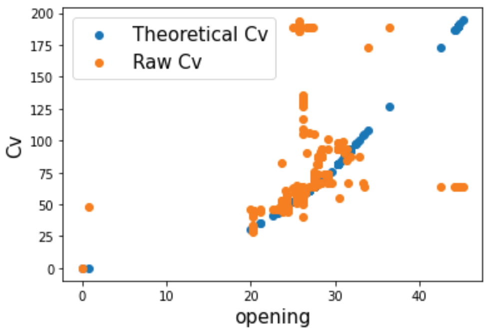

Fig. 4.: Raw Cv (orange) versus theoretical Cv (blue points). The date of the data is masked.

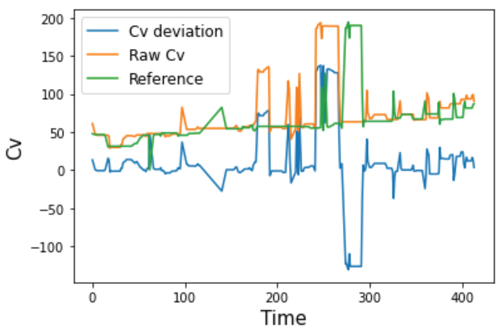

Fig. 5.: Raw Cv (orange), theoretical Cv (green) and Cv deviation (blue) plotted against time. The valve opening information is masked.

We did not consider the case where g depends on process parameters, since the observation times are far from evenly-spaced. Also, the piecewise linear modeling of f is excluded in this example because no apparent break point is observed. Following Algorithm 1, optimal polynomial orders are found as $p^* = 1, q^* = 1$, which means f and g are straight lines: $f(h) = -4.63h$, and $g(h) = 0.24 - 0.006h$.

In Figure 6, f_0 is shown by the red dash-dotted line. According to g, the daily Cv deviation should be around 0.12 at opening 20%, and 0.04 at 32%. The standard deviations of the parameters for f and g are respectively 0.92 and [0.09, 0.003]. The second best model is configuration $p = 2, q = 0$. The corresponding ICDC is drawn with the blue dashed line in Figure 6, with $f(h) = 2.82h - 0.16h^2$, and $g(h) = 0.073$.

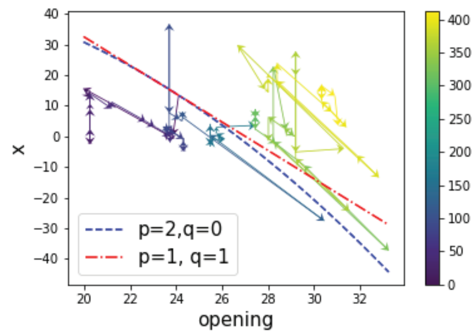

Fig. 6.: The evolution of Cv deviation curves as a function of time is visualized by colored vectors. Red and blue lines represent the two estimated most likely ICDC: a straight line (red) or a parabola (blue).

We can then compute the adjusted Cv deviation for an arbitrary opening h based on f_0, $\boldsymbol{\delta}$ and g using Eq.(4). Let $h = 26\%$. In Figure 7, the orange points show the raw Cv deviation. The 0.05 and 0.95 quantiles of adjusted Cv deviation are drawn in blue and filled in between. The blue solid line and the orange dashed line show the trends (computed by Nadaraya–Watson estimator). Clearly, the erosion is more severe at $h = 26\%$ than what the raw measurements suggest.

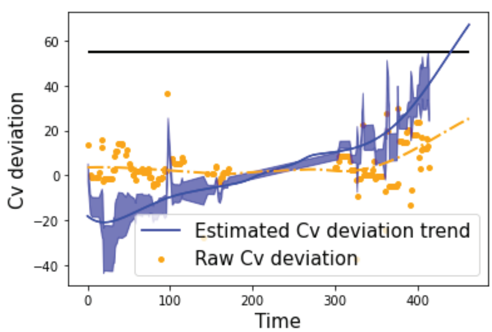

Fig. 7.: The adjusted and raw Cv deviation.

Finally, in Figure 8, we can plot the smoothed Cv deviation surface. The green points are the raw Cv deviation plotted against time and opening. The surface is obtained by calculating the Cv deviation growth trend (using the Nadaraya–Watson estimator as we did in Figure 7) for each opening inside the opening range. This is an estimation of the erosion ground truth $y(t,h)$ based on the raw measurements.

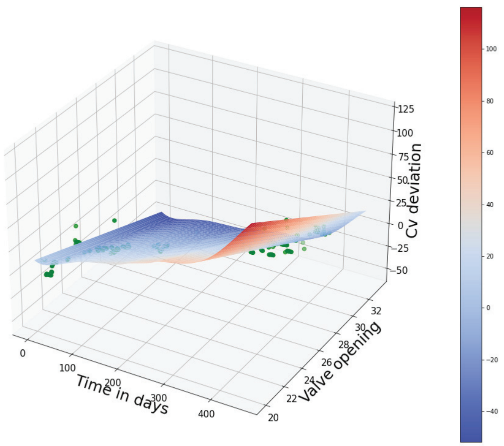

Fig. 8.: Smoothed Cv deviation surface.

5. Conclusions

We reveal some common pitfalls in using Cv monitoring data to evaluate the health state of choke valves. The erosion is not monotonic, and the Cv data should be considered in combination with historical valve opening data. We present a model for adjusting the raw Cv measurement based on valve opening and process parameters. The results improve the estimation of the choke valve's erosion state and can provide insights for decision makers in production and maintenance.

Nevertheless, the model assumes a deterministic relationship between the valve opening and Cv deviation. For future work, stochastic models that loosen this assumption are worth investigating. In particular, the valve is operating in a changing working condition (opening), which not only determines the observed Cv but can also influence the erosion growth. Thus, a state-space model may be a good choice for describing the erosion process. Finally, sand data, if accessible, should be taken into account since they can also influence the amplitude of Cv deviation.

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