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Control Performance Monitoring of Excessive Oscillations of an Offshore Production Facility ⋆

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Abstract: In remote operation of offshore platforms, real time control systems must be well maintained for efficient and safe operations. Early detection of control and equipment performance degradation is critical and is the foundation for implementing higher level integrated optimization. Poor control performance is usually the result of undetected deterioration in control valves, inadequate performance monitoring, and poor tuning in the controllers. In this work, data-driven approaches to monitoring control performance are applied to an offshore platform. The minimum variance control benchmark for single loops and the covariance benchmark for multi-loops are used to detect deteriorated control variables. The covariance benchmark is used to determine the directions with significantly worse performance versus the benchmark. To detect valve stiction, the Savitzky-Golay smoothing filter is combined with a curve fitting method. The Savitzky-Golay filter has the advantage of preserving features of the distribution such as relative maxima, minima and widths. A stiction index is used to indicate whether a valve stiction occurred. The OSIsoft PI system is suggested as the implementation platform. Real-time data can be exchanged between PI and MATLAB via OPC interface.

Keywords: Valve stiction detection; Savitzky-Golay smoothing filter; oil production; control performance monitoring

1. INTRODUCTION

Control system performance is a critical component of offshore platform operations. Control systems must perform well to attain maximum performance, reliability, regulatory compliance, and safety. In the multi-level integrated optimization hierarchy, real time control systems work at the fastest time scale (Foss and Jensen (2011)), which are the best place for early event detection and are the foundation for implementing higher level advanced decision environment.

However, even in the well-maintained industrial processes it is typical that as much as one third of the controller perform poorly and only one third of the controllers work near their optimal settings. Poorly conditioned control systems consume more energy, wear out equipment faster, lead to more waste, and make higher level data analysis and decision making unreliable. The objective of control systems health monitoring is to make sure that controllers perform at their best capability to maintain the process to the set point and minimize undesirable disturbances to the operations of other processes upstream or downstream of the controller. Early work in the general control performance monitoring literature can be found in Harris (1989), Huang et al. (1997), and Qin (1998). Some work in the detection and diagnosis of oscillations in control loops can be found in Taha et al. (1996), Miao and Seborg (1999), Thornhill et al. (2003b) and Thornhill et al. (2003a). Applications of the control performance monitoring techniques have been reported. For example, Huang and Shah (1997) assessed control loop performance on a paper-machine headbox; Yuan et al. (2009) applied the control performance assessment techniques on a furnace control process; Morris and Zhang (2009) examined the control performance of a biotechnological process; Thornhill et al. (1999) reported application of control loop performance assessment in a refinery setting.

Although great success of control performance monitoring has been reported in numerous industries, relative little work is reported for upstream oil production facilities, especially for offshore oil platforms. To maintain optimum control performance for offshore platforms, control loop performance needs to be monitored remotely and with high assurance to achieve stringent maintenance and avoid unnecessary dispatching of maintenance personnel to the platforms. This can be achieved by diagnosing the root

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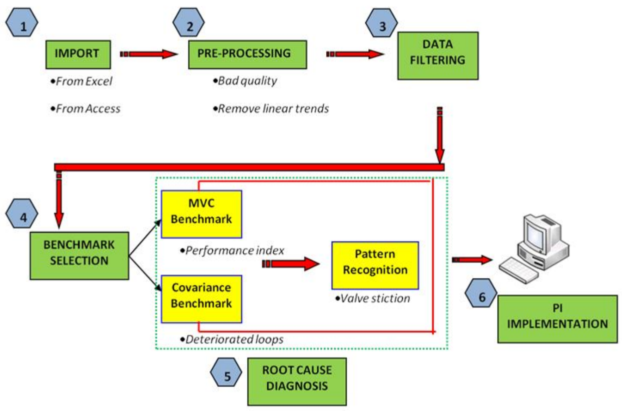

Fig. 1. Our Proposed Framework

causes of poor performance, assessing the degree of degradation remotely, and taking appropriate corrective recommendations when poor performance is detected. However, the detection, diagnosis and resolution of these problems are difficult, particularly in large and complex offshore platforms.

The objective of this work is to mitigate this problem by monitoring the performance of control loops using data-driven methods. The desirable approach would be to identify several aspects of poor control performance and generate a list of problematic loops with diagnoses of the individual problems so that these can be prioritized and corrected. The proposed framework is shown in Fig. 1.

The framework includes six steps. The first three steps are importing, pre-processing and filtering the data. Then a benchmark, e.g., the minimum variance control benchmark by Harris (1989), for single loops and the covariance benchmark for multi-loops are used to detect deteriorated control variables (Yu and Qin (2008a)). The curve fitting method proposed by He et al. (2007), which is one type of pattern recognition, is used to detect valve stiction.

To make them as a user-friendly tool for the engineers, we suggested the OSIsoft PI system as the implementation platform. PI system is a process historian, which gathers event-driven data, in real-time, from multiple sources across the plant and/or enterprise. The reasons for choosing PI are: existing PI infrastructure eliminates additional capital expense; engineers are familiar with PI system; there is zero additional capital cost associated with PI; and there is zero risk. The PI-ACE (advanced computing engine) allows programming of complex calculations, and it can be used in VB.NET development environment, which provides the ability to call COM and .NET objects and a library of user-written functions. Therefore, we suggested developing PI-ACE module in VB.NET development environment, and the module has the capability to call a library of our written MATLAB functions. Real-time data could be exchanged between PI and MATLAB via OPC interface with MATLAB OPC toolbox and PI DA/HDA Server.

This article is organized as follows. The use of a covariance benchmark to detect deteriorated control variables in multi-loops is described in Section 2. An integration of the Savitzky-Golay filter and the curve fitting method to detect valve stiction is developed in Section 3. Results on control performance monitoring of an offshore platform are shown in Section 4. Section 5 concludes the paper.

2. COVARIANCE BENCHMARK FOR MULTI-LOOPS

2.1 Data-driven covariance benchmark

Yu and Qin (2008a) proposed a data-based covariance benchmark for control performance monitoring. Within the covariance monitoring scheme, a period of "golden" operation data is used as a user-specified benchmark, and generalized eigenvalue analysis is used to extract the directions with the degraded control performance against the benchmark. The confidence intervals for the population eigenvalues are derived on the basis of their asymptotic distribution. This can be used to determine the directions or subspaces with significantly worse performance versus the benchmark. The covariance-based performance indices within the isolated worse performance subspaces are then derived to assess the performance degradation.

Let the benchmark period be I and the monitored period be II, then the direction along which the largest variance ratio of the monitored period versus the benchmark period is:

$$p = \arg\max \frac{p^T \mathrm{cov}(y_{\mathrm{II}})p}{p^T \mathrm{cov}(y_{\mathrm{I}})p} \quad (1)$$

The solution of the above equation is equivalent to the following generalized eigenvalue analysis:

$$\mathrm{cov}(y_{\mathrm{II}})p = \lambda \mathrm{cov}(y_{\mathrm{I}})p \quad (2)$$

Where λ is the generalized eigenvalue and p is the corresponding eigenvector. The eigenvector corresponding to the largest generalized eigenvalue $\lambda_{\max}$ represents the direction of the largest variance inflation in the monitored period against the benchmark period. This direction is referred to as worst performance direction.

The covariance performance index is defined as:

$$I_v = \frac{|\mathrm{cov}(y_{\mathrm{II}})|}{|\mathrm{cov}(y_{\mathrm{I}})|} \quad (3)$$

Where $|\cdot|$ is the determinant.

It can be further derived as:

$$I_v = \frac{|\mathrm{cov}(y_{\mathrm{II}})|}{|\mathrm{cov}(y_{\mathrm{I}})|} = |\Lambda| = \prod_{i=1}^{q} \lambda_i \quad (4)$$

To examine the significance of population eigenvalues λ_i with respect to the threshold value one, the confidence intervals for the population eigenvalues are derived on the basis of their asymptotic distribution. The lower bound and the upper bound of the confidence interval are denoted as $L(\lambda_i)$ and $U(\lambda_i)$. If the lower bound $L(\lambda_i) > 1$, then the control performance of the monitored period is worse than that of the benchmark period.

2.2 Angle-based contribution for diagnosis

To identify the controlled variables responsible for performance degradation, Yu and Qin (2008b) proposed to examine the angle between each individual variable and the worse performance subspace. The cosine of the angle is defined as the contribution index. If the index is close to one, it indicates that the angle approaches zero and the variable is virtually in the worse subspace. Then the corresponding controlled variable contributes significantly to the performance degradation. If the index is zero, the angle is 90° and the corresponding controlled variable has no contribution to the worse subspace. A threshold value of the angle 45° is selected.

The contribution index is denoted as $\cos(\theta_k)$. It is defined as:

$$\cos(\theta_k) = \frac{\| \hat{e}_k \|}{\| e_k \|} = \| \hat{e}_k \| \tag{5}$$

Where $e_k = [0 \cdots 0_{k-1} \quad 1 \quad 0 \cdots 0]^T$ is the k^{th} unit vector and represents the k^{th} controlled variable. $\hat{e}_k$ is the projection of unit vector e_k onto the worse subspace P.

It can be further derived as:

$$\cos(\theta_k) = \left\| (\tilde{P}^T \tilde{P})^{-\frac{1}{2}} (\tilde{P}^T e_k)(e_k^T e_k)^{-\frac{1}{2}} \right\| \tag{6}$$

Where $\tilde{P}$ is the orthonormal basis transformed from P.

The confidence interval could be derived from the asymptotic statistics of canonical correlation. Then, if the index is larger than the upper bound of the interval, the corresponding variable can be determined as a contributor to the worse subspace.

3. VALVE STICTION DETECTION

Oscillations may be a very drastic form of plant performance degradation in the process industries. Oscillations in control loops may be caused either by aggressive controller tuning, disturbances, or the presence of nonlinearity, such as static friction, dead-zone, and hysteresis. Valve stiction is the most severe source of oscillations. He et al. (2007) proposed the use of curve fitting method for the isolation of oscillations due to sticking valves from those due to control instability or external disturbances. Valve stiction tends to cause a triangular type of oscillation after an integrating element, while aggressive controller tuning and external oscillating disturbances tend to cause a sinusoidal wave after an integrating element.

In our work, we combine the Savitzky-Golay smoothing filter and curve fitting method to detect valve stiction.

3.1 Savitzky-Golay smoothing filter

The field data are noisy. The premise of data smoothing is that one is measuring a variable that is both slowly varying and also corrupted by random noise.

The Savitzky-Golay smoothing filter was first described by Savitzky and Golay (1964). The Savitzky-Golay method essentially performs a local polynomial regression on a series of values to determine the smoothed value. The main advantage of this approach is that it tends to preserve features of the distribution such as relative maxima, minima and width, which are usually 'flattened' by other adjacent averaging techniques.

To illustrate the Savitzky-Golay method, consider the specific example in which five data are used to approximate a quadratic polynomial. The polynomial can be expressed in the form:

$$poly(i) = a_0 + a_1 i + a_2 i^2 \tag{7}$$

Where the coefficients a_0, a_1 and a_2 are determined from the simultaneous equations in which the abscissa i is the index of for the data. The origin is always placed at the central data and so the abscissa values corresponding to each of the data are $\{-2, -1, 0, 1, 2\}$:

$$\begin{bmatrix} 1 & -2 & 4 \\ 1 & -1 & 1 \\ 1 & 0 & 0 \\ 1 & 1 & 1 \\ 1 & 2 & 4 \end{bmatrix} \begin{bmatrix} a_0 \\ a_1 \\ a_2 \end{bmatrix} = \begin{bmatrix} f_{-2} \\ f_{-1} \\ f_0 \\ f_1 \\ f_2 \end{bmatrix} \tag{8}$$

Or

$$Aa = f \tag{9}$$

Where the evenly spaced data $\{f_{-2}, f_{-1}, f_0, f_1, f_2\}$ are selected with the target of replacing the value for f_0 with the value for the polynomial at $i = 0$ or $poly(0) = a_0$. The coefficients to the polynomial are determined in the least-squares sense. The normal equation is:

$$A^T A a = A^T f \tag{10}$$

Or

$$a = (A^T A)^{-1} A^T f \tag{11}$$

The top row of $(A^T A)^{-1} A^T$ yields the prescription for computing the value of a_0, namely:

$$a_0 = [\, s_0 \ s_1 \ s_2 \ s_3 \ s_4 \,] \begin{bmatrix} f_{-2} \\ f_{-1} \\ f_0 \\ f_1 \\ f_2 \end{bmatrix} \tag{12}$$

Thus, for each set of five such data, the central data can be replaced by the value determined for a_0.

3.2 Curve fitting method

According to He et al. (2007), in the case of control-loop oscillations caused by controller tuning or external oscillating disturbances, the controller output (OP) and process variable (PV) typically follow sinusoidal waves for both self-regulating and integrating processes. In the case of stiction, for self-regulating processes, the PI controller acts as the first integrator and the OP's move follows a triangular wave, whereas for integrating processes such as level control, the PV signal follows a triangular wave.

In our work, the raw data of OP or PV were treated with Savitzky-Golay smoothing filter first, and then curve fitting method was applied to detect valve stiction.

Both sinusoidal fitting and triangular fitting were performed to the smoothed data. The mean squared errors for both fitting methods were calculated. Then a stiction index was defined as the ratio of the MSE value of the

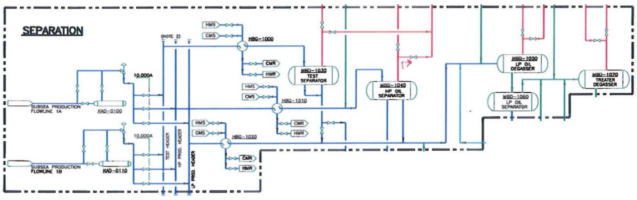

Fig. 2. Offshore production facility separation unit

sinusoidal fitting to the summation of the MSE values of both the sinusoidal and triangular fittings:

$$\mathrm{SI} = \frac{\mathrm{MSE_{Sin}}}{\mathrm{MSE_{Sin}} + \mathrm{MSE_{Tri}}} \tag{13}$$

The following rules were recommended:

$$\begin{aligned} \mathrm{SI} \leq 0.4 &\quad \Rightarrow \quad \text{no stiction} \\ 0.4 < \mathrm{SI} < 0.6 &\quad \Rightarrow \quad \text{undetermined} \\ \mathrm{SI} \geq 0.6 &\quad \Rightarrow \quad \text{stiction} \end{aligned} \tag{14}$$

4. RESULTS

An offshore platform was studied by using the above mentioned performance assessment approaches. The operating data were collected from the production facility under closed-loop operation. The data were collected on a five second basis. The production facility consists of five major units: Separation, Compression, Oil treating, Water treating, and HP/LP flare. We focused on the loops that were considered the most important for optimizing the production.

4.1 Single loop monitoring by minimum variance control benchmark

The separation unit of the offshore platform was investigated. Fig. 2 shows the process flow diagram. There are six key control loops in this unit. The detailed description for these control loops is given in Table 1.

Table 1. The description of control loops from the separation unit

Loop ID	Category	Description
Loop 1	Pressure control	Test separator backpressure control
Loop 2	Temperature control	Test separator inlet temperature control
Loop 3	Temperature control	HP oil separator inlet temperature control
Loop 4	Temperature control	LP oil degasser inlet temperature control
Loop 5	Pressure control	Treater degasser backpressure control
Loop 6	Temperature control	Oil treater outlet temperature control

According to the feedback invariance law, for a system with time delay, a portion of the output variance is feedback control invariant. This portion of the output variance equals the variance achieved under the minimum variance control.

The performance index is defined as:

$$\eta = \frac{J_{mv}}{\mathrm{var}(y)} \tag{15}$$

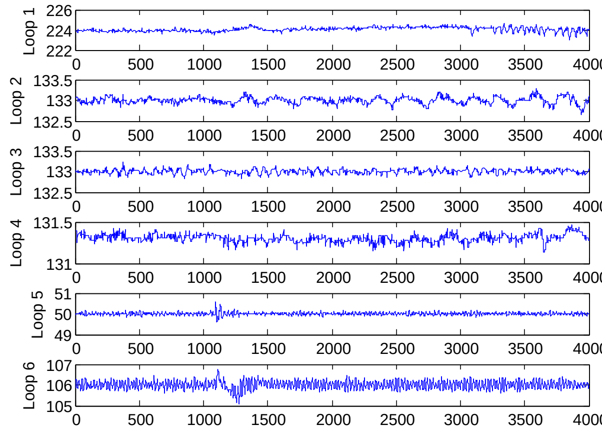

Fig. 3. Process variable plots for the six loops in the separation unit

Where J_{MV} is the minimum variance.

If the index is close to 1, then further reduction in the output variance is not possible by re-tuning the controller, and the output variance can be reduced by process re-engineering. If the index is close to 0, then there is high potential for reducing the output variance by re-tuning the existing controller. And $(1 - \eta)$ would represent the potential for improvement.

Harris (1989) showed the possibility of estimating the minimum variance from routine operating data. Many researchers further developed the technique. In this work, we used the FCOR approach proposed by Huang and Kadali (2008). The procedures are as follows: 1. A set of data points were extracted during the routine operation; 2. A time series model was estimated from this set of data; 3. Specify a time delay d according to a priori process knowledge; 4. Get the impulse response model from the model obtained in step 2; 5. Calculate the minimum variance from the first d terms of the impulse response model and the noise variance.

The process variable plots for the six loops in the separation unit are shown in Fig. 3. The MVC benchmark monitoring results are shown in Table 2 and Fig. 4. In Fig. 4, the blue part represents the performance index η, and the green part is $(1-\eta)$. For example, for Loop 2, the performance index of 0.49 implies that current variance can be potentially reduced by a factor of 0.51 if an optimal tuning is implemented. Loop performance measure could be ranked and classified. The results indicated that Loops 1,3 and 5 had a good performance of current loop tunings, and there was little potential for further reduction in process variance by adjusting or re-designing the controller. Loop 6 had a small index of 0.31, therefore, it needed attention and further diagnosis. Further diagnosis of the oscillation behavior of loop 6 will be shown in subsection 4.3.

4.2 Multi-loops monitoring by covariance benchmark

Besides the separation unit, the VRU compression&gas export unit is another important unit on the offshore production facility. Therefore, the VRU compression&gas export unit was investigated in this subsection using

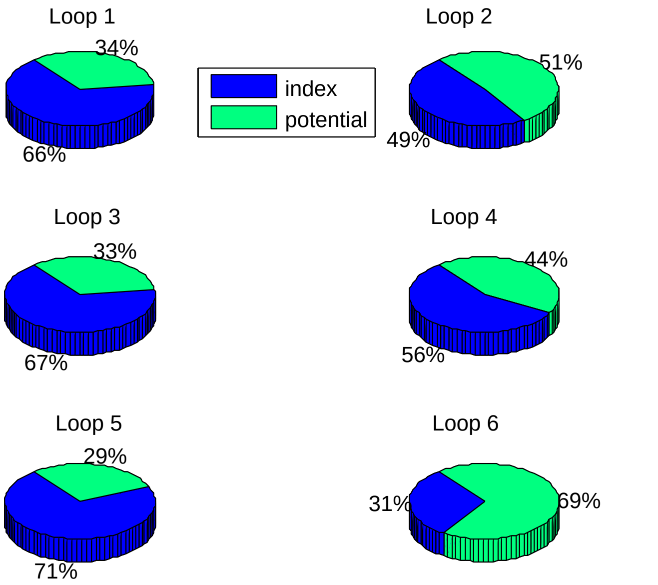

Fig. 4. MVC benchmark monitoring results for the six loops in the separation unit

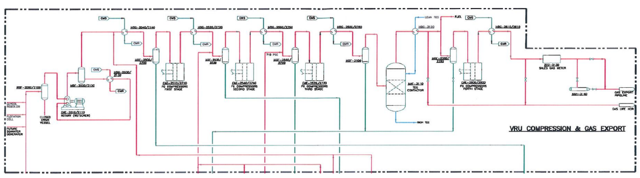

Fig. 5. Offshore production facility VRU compression&gas export unit

covariance benchmark. Fig. 5 shows the process flow diagram. There are seven key control loops in this unit. The detailed description for these control loops is given in Table 3.

A period of good operation data (2000 samples) was set as the benchmark data, and then another period of data (2000 samples) was monitored. The process variable plots for the seven loops in the VRU compression&gas export unit are shown in Fig. 6.

The generalized eigenvalue analysis between the covariance matrices of the benchmark data and the monitored data was performed. The full spectrum of sample eigenvalues in descending order and the corresponding cumulative percentages are shown in Fig. 7.

The calculated overall performance index I_v is 29.68, and thus the volume of the monitored data is 29.68 times of the benchmark data. It implies that the overall control performance of the monitored period is inferior to the performance of the benchmark period. When looking at each individual eigenvalue in Fig. 7, it can be found that the control performance is degraded along some directions.

Table 2. MVC benchmark monitoring results for the six loops in the separation unit

Loop ID	1	2	3	4	5	6
η	0.6637	0.4879	0.6701	0.5643	0.7086	0.3054
J_{mv}	0.0292	0.0031	0.0017	0.0012	0.0031	0.0114
var(y)	0.0440	0.0063	0.0026	0.0020	0.0043	0.0373

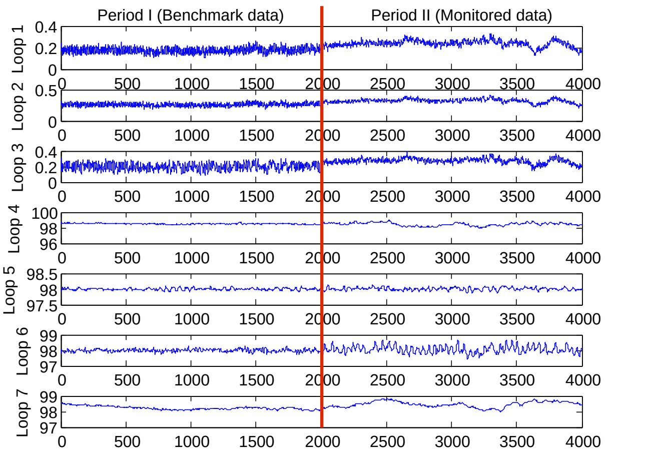

Fig. 6. Process variable plots for the seven loops in the VRU compression&gas export unit

The maximum eigenvalue is 17.57, which means the variance along the first eigenvector direction is increased by a factor of 17.57. Therefore, the control performance of the monitored period is significantly worse than that of the benchmark period along this eigendirection.

The benchmark data and the monitored data were projected to the first eigendirection. In Fig. 8, the monitored period exhibits larger variation than the benchmark period along the first eigendirection. The corresponding largest eigenvalue 17.57 reflects the variance ratio of the projected data along this direction. These variance changes cannot be easily seen in the original data in Fig. 6, which shows the effectiveness of the covariance-based performance monitoring method.

Table 3. The description of control loops from the VRU compression&gas export unit

Loop ID	Category	Description
Loop 1	Pressure control	VRU Compressor Suction to LP Flare Pressure Control
Loop 2	Pressure control	VRU Compressors Suction Pressure Control
Loop 3	Pressure control	VRU Compressor Suction Scrubber #2 Recycle Pressure Control
Loop 4	Temperature control	Flash Gas Compressor #1 3rd Stage Discharge Temperature Control
Loop 5	Temperature control	Flash Gas Compressor #1 4th Stage Discharge Temperature Control
Loop 6	Temperature control	Flash Gas Compressor #2 3rd Stage Discharge Temperature Control
Loop 7	Temperature control	Flash Gas Compressor #2 4th Stage Discharge Temperature Control

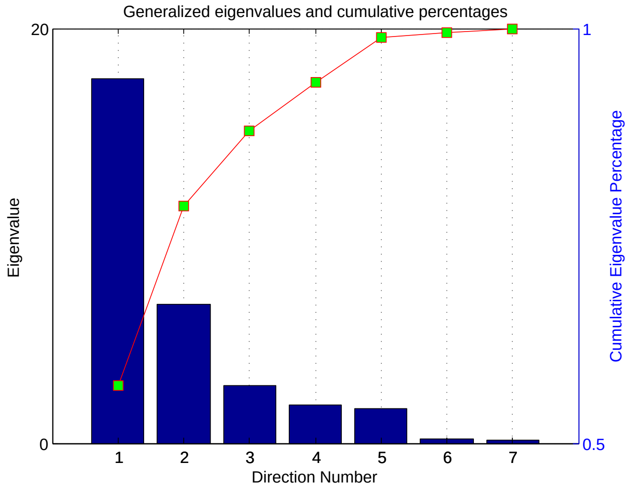

Fig. 7. Covariance-based generalized eigenvalue analysis results for the monitored data against the benchmark data: full eigenvalue spectrum and the corresponding cumulative percentages

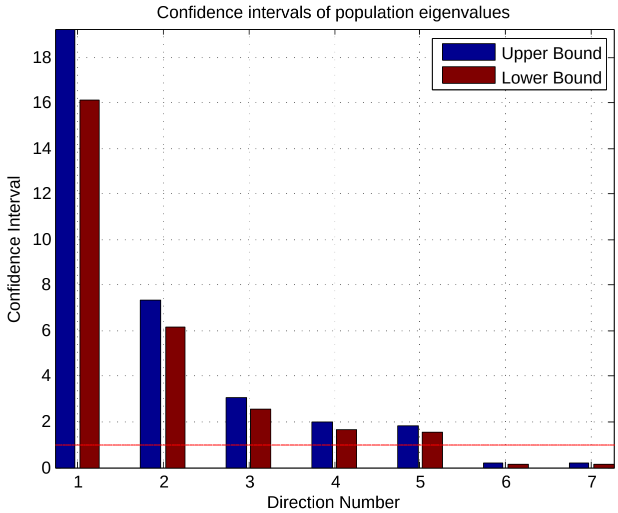

Fig. 9. The 95% confidence intervals for population eigenvalues

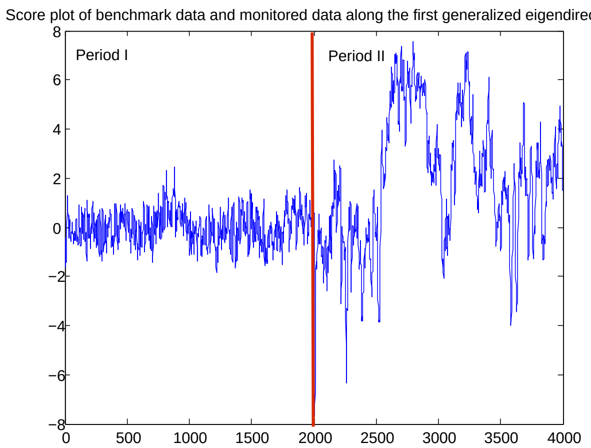

Fig. 8. Projected score plots of benchmark data and monitored data along the first generalized eigendirection

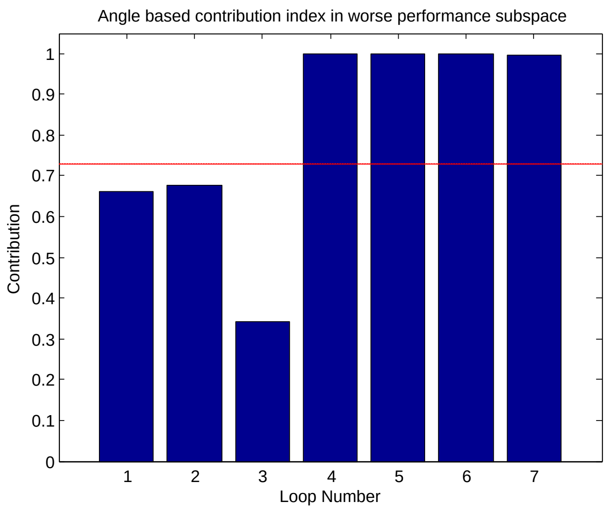

Fig. 10. Angle based contribution charts with 95% confidence limits in the worse performance subspace of period II over benchmark period I

The computational results for the confidence intervals of population eigenvalues are shown in Fig. 9. It can be seen that the lower bounds of eigenvalues for the first five eigendirections exceed the threshold value line. Consequently, the first five eigendirections are determined as the worse directions.

To diagnose and identify which loops contributed to the worse subspace, the angle based contribution chart was implemented. The angle based contribution chart within the worse performance subspace is shown in Fig. 10. It can be seen that the contribution index values of Loops 4, 5, 6, and 7 exceed the 95% control limit. Therefore, these four loops contributed significantly to the worse performance, and these four loops are determined as degraded loops.

4.3 Detecting valve stiction in oscillation loops

In subsection 4.1, loop 6 in the separation unit was detected to have a deteriorated performance with a small MVC index of 0.31, and this loop exhibited a oscillatory behavior. Therefore, we further diagnosed this loop to determine whether a valve stiction occurred.

A set of 1500 samples of the controller output (OP) were collected from this loop. A portion of the OP is shown in Fig. 11. A Savitzky-Golay smoothing filter with order 3 and window size 41 was applied to this set of data. And then curve fitting method was applied on both raw data and smoothed data. The stiction indices for both the raw data and smoothed data are shown in Fig. 12. The stiction index of the raw data is 0.5001, which falls into the grey area of between 0.4 and 0.6. The stiction index of the smoothed data is 0.6248, and it indicates that a valve stiction occurred in this loop. Therefore, the Savitzky-Golay smoothing filter helps to distinguish this kind of marginal data and increases the stiction index when valve stiction occurs.

Another two oscillatory loops in the offshore production facility were examined as well. We denoted these two loops as Loop A and Loop B. Curve fitting results on the smoothed data are shown in Fig. 13. It is clear that OP

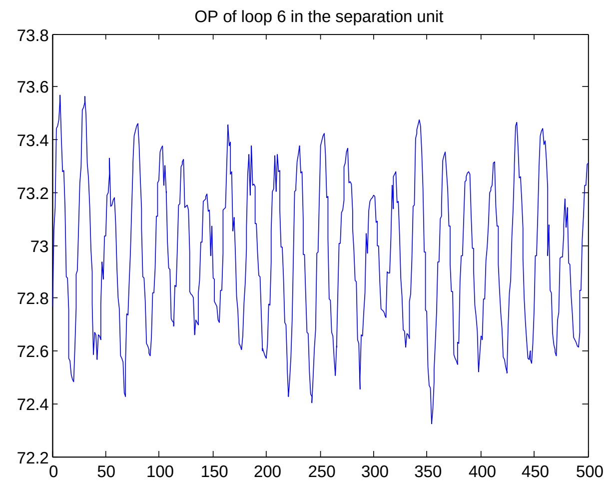

Fig. 11. A portion of the controller output of loop 6 in separation unit

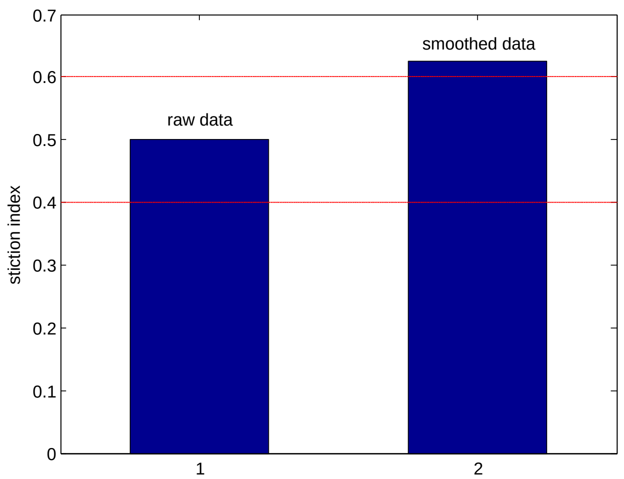

Fig. 12. Stiction index on both raw data and smoothed data for loop 6 in the separation unit

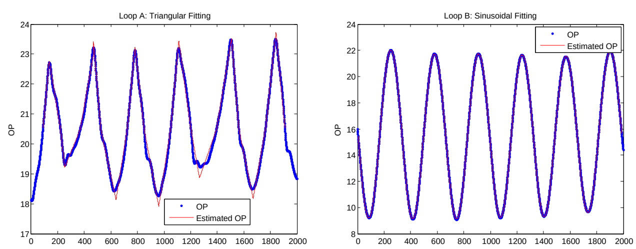

Fig. 13. Curve fitting results on smoothed data: (Left) Triangular fitting for loop A and (Right) Sinusoidal fitting for Loop B

of loop A follows a triangular wave, while OP of loop B follows a sinusoidal wave.

Table 4.

Loop ID	SI (raw data)	SI (smoothed data)	Whether stiction
Loop 6	0.5001	0.6248	stiction
Loop A	0.8089	0.8132	stiction
Loop B	0.0116	0.0098	no stiction

The stiction indices for all the above three oscillatory loops are listed in Table 4. The stiction indices on smoothed data of loops A and B are 0.8132 and 0.0098, respectively. That indicates that oscillation in loop A was caused by valve stiction, and oscillation in loop B was caused by unstable controller or external disturbance. The stiction indices on the raw data of loops A and B are 0.8089 and 0.0116, respectively. Compared to the stiction index on the smoothed data, it can be seen that the Savitzky-Golay smoothing filter helps to increase the stiction index when valve stiction occurs, and helps to decrease the stiction index when there is no stiction.

5. CONCLUSION

Data-driven methods have been successfully applied on the offshore platform control performance assessment and monitoring in this paper. Minimum variance benchmark or a covariance benchmark is used. For the covariance benchmark, generalized eigenvalue analysis is performed to find the directions with the worst control performance in the monitored period versus the benchmark period. Angle based contribution is used for control performance diagnosis. The Savitzky-Golay smoothing filter combined with curve fitting method has been developed to detect valve stiction. A better fit to a triangular wave indicates valve stiction, and a better fit to a sinusoidal wave indicates non-stiction.

The results in this paper demonstrate the effectiveness of these approaches. 15 key control loops, which are considered most important for higher level production optimization, are examined. The data-driven benchmark based statistical performance monitoring approach successfully determined directions with worse control performance in the monitored period against the benchmark period. The angle based contribution successfully determined loops with degraded performance. The combination of Savitzky-Golay smoothing filter and curve fitting method successfully detects valve stiction. The Savitzky-Golay smoothing filter helps to improve the effectiveness by increasing the stiction index when valve stiction occurred, especially when the stiction index of the raw data falls into the grey area.

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