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# Health-Aware Operation of a Subsea Compression System Subject to Degradation

Adriaen Verheyleweghen[a], Julie Marie Gjøby[a] and Johannes Jäschke[a,*]

[a]*Dept. of Chemical Engineering, NTNU, N-7491 Trondheim, Norway*
*jaschke@ntnu.no*

## Abstract

We propose an health-aware operation approach for combining short-term control objectives with long-term profit and reliability targets. In particular, we present a hierarchical approach for operating a compressor subject to degradation. We consider a case study of a subsea compressor, where the goal is to maximize the gas throughput, while ensuring that the compressor can be operated continuously until a planned maintenance stop. In the top layer, we repeatedly solve a dynamic optimization problem to find the optimal long-term operation strategy, subject to load-induced compressor degradation. The supervisory control layer below receives the computed setpoints and operational parameters, and applies them in a self-optimizing control structure to ensure near-optimal operation in the presence of disturbances. The regulatory control layer in the bottom stabilizes operation in an otherwise unstable operating region (surge). We show the efficacy of our health-aware operation approach by comparing it to traditional control structures where the equipment health is not explicitly considered as part of the production optimization. Our approach results in higher average production, without jeopardizing the health of the system.

**Keywords:** Health-aware operation, Contol, Reliability, Optimal Operation, Rotating Machinery

## 1. Introduction

Unplanned maintenance intervention of subsea systems are costly, so it is necessary to ensure that operation does not reduce the system reliability to unacceptable levels. Traditionally, this has been achieved by introducing large safety margins and enforcing conservative operational strategies. Better economical performance can be achieved by employing prognostics and health monitoring (PHM), which means that the system state is monitored and projected into the future. A natural extension of PHM is health-aware control, in which we combine control and reliability objectives, yielding a control structure that maximizes plant profitability while keeping the plant health within acceptable limits (Sanchez et al., 2015; Verheyleweghen and Jäschke, 2017).

Health-aware control is achieved by repeatedly solving a shrinking horizon dynamic optimization problem to find an operating strategy based on the current compressor health and its predicted development. The time horizon is from the present until the next planned maintenance intervention, and the objective is to maximize the profit subject to health constraints. The dynamics of this layer are on the time-scale of weeks to months. On a more frequent basis, disturbances are rejected by a supervisory control layer in order to keep operation close to the desired (optimal) operating point. We use self-optimizing control ideas (Skogestad, 2000) to achieve this. The lowest and fastest control layer is in charge of surge control. Surge is an unwanted mode of operation characterized by limit-cycle oscillations in flow and pressure, which can harm the internals of the compressor (McMillan, 1983). Traditionally, operation is restricted by a generous safety margin from the surge line. However, it is often desirable to operate closer to the surge line, as this leads to increased efficiency and lower operating costs. An alternative to surge avoidance is active surge control. For this purpose, a close-coupled valve (CCV) is introduced to the system. Using the CCV, we can control the compressor characteristic, thereby stabilizing operation in an otherwise unstable region (Gravdahl and Egeland, 1999). A feedback linearizing controller proposed by Backi et al. (2016), is used for this purpose. An illustration of the proposed control structure is shown in Figure 1.

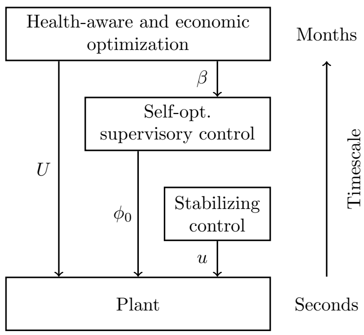


Figure 1: Multi-layer control structure for stable, health-aware operation.

The main contributions of this paper are the following: 1) We propose a three level control structure for health-aware control of a compression system. 2) We show that the method outperforms traditional control methods

## 2. Model description

### *2.1. Short timescale dynamics: Surge*

The surge model used here is that of a centrifugal compressor with an added CCV for surge control, which as described by Simon (1993). We use the transformed version of the model presented by Gravdahl and Egeland (1999), by which the system can be described in terms of the non-dimensional compressor mass flow $\phi$ and the non-dimensional pressure rise across the plenum, $\psi$. A detailed description and derivation of the model is given in Gravdahl and Egeland (1999), but a summary is given below for completeness. An illustration of the system is given in Fig. 2. Three degrees of freedom are available for control in the system: the compressor speed, the CCV opening and the throttle opening.

The two-state Greitzer model is given as:

$$\dot{\hat{\phi}} = B\left[\hat{\Psi}_C\left(\hat{\phi}\right) - \hat{\psi} - u\right] \quad (1)$$

$$\dot{\hat{\psi}} = \frac{1}{B}\left[\hat{\phi} - \hat{\Phi}_T\left(\hat{\phi}\right)\right], \quad (2)$$

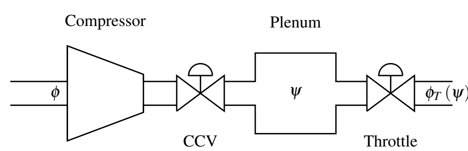


Figure 2: Flowsheet of the Greitzer compressor model

where the $(\hat{\cdot})$-symbol is used to denote deviation from the specified operating points, $\hat{\phi} = \phi - \phi_0$ and $\hat{\psi} = \psi - \psi_0$. $(\phi_0, \psi_0)$ is the specified operating point. In the above expression, $B$ is the Greitzer parameter, which is proportional to the compressor blade tip speed $U$, $B = kU$, where $k$ is a geometry-dependent constant. $\hat{\Psi}_C$ is the cubic approximation of the axisymmetric compressor characteristic, $\hat{\Phi}_T$ is the throttle characteristic, and the input $u$ is the pressure drop across the CCV (as determined by its opening). The compressor and throttle characteristics is shown in Figure 3.

The compressor characteristic $\hat{\Psi}_C$ indicates the pressure rise for a given flow, and is unique for every compressor. The characteristic is approximated by the cubic

$$\hat{\Psi}_C\left(\hat{\phi}\right) = -k_3\hat{\phi}^3 - k_2\hat{\phi}^2 - k_1\hat{\phi}, \quad (3)$$

where $k_1 = \frac{3H\phi_0}{2W^2}\left(\frac{\phi_0}{W} - 2\right)$, $k_2 = \frac{3H}{2W^2}\left(\frac{\phi_0}{W} - 1\right)$ and $k_3 = \frac{H}{2W^3}$. $H$ and $W$ are equipment-specific parameters relating to the peak and valley points of the compressor characteristic. The peak point, $(\phi^*, \psi^*) = (2W, \psi^*)$, is assumed to be the surge point, with all points left of the peak being unstable.

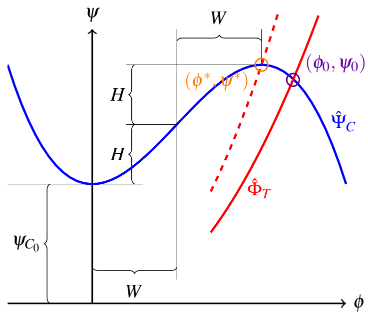


Figure 3: Cubic approximation of the axisymmetric compressor characteristic (blue) and the throttle characteristic (red). The operating point $(\phi_0, \psi_0)$ is shown in purple and the surge point $(\phi^*, \psi^*) = (2W, \psi^*)$ is shown in orange. The surge line (surge point at various compressor speeds) is shown as the dashed line.

The throttle characteristic is given as

$$\hat{\Phi}_T(\hat{\psi}) = \frac{\phi_0}{\sqrt{\psi_0}}\left(\mathrm{sign}(\psi)\sqrt{|\psi|} - \sqrt{\psi_0}\right). \tag{4}$$

The intersection between $\hat{\Psi}_C$ and $\hat{\Phi}_T$ gives the operating point $(\phi_0, \psi_0)$, shown in purple in Figure 3.

### *2.2. Long timescale dynamics: Compressor degradation*

Variations in pressure and flow rate (as caused by surge) lead to radial vibrations, axial thrust displacement and a large temperature rise. This will in turn damage bearings, blades and other internal components (McMillan, 1983). We lump the accumulated damage on all internal components into a health indicator state $x$, whose propagation is modeled as

$$\dot{x} = \mathbb{E}\left(p_1\phi_0 + \int_0^\infty \left(p_2\left|\hat{\phi}(d)\right| + p_3\left|\dot{\hat{\phi}}(d)\right|\right) dt\right), \tag{5}$$

where $\mathbb{E}$ is the expected value operator, $d = \begin{bmatrix} W & H & \psi_{C_0}\end{bmatrix}^\mathsf{T}$ are independently normal distributed disturbances and $p_i$ are weights. The $p_1$-term is the damage caused by regular operation, which is proportional with the throughput. The harder the compressor is run (in terms of throughput), the more rapidly it degrades. The $p_2$-term is damage caused by oscillations in pressure and flow, caused by surge. The $p_3$-term accounts for high-frequency oscillations, as these are thought to be more harmful to the compressor than low-frequency oscillations.

## 3. Hierarchical control structure for the subsea compressor

Due to the large difference in time scales for the problem, it is natural to divide it into several timescale-separated layers. The lowest layer stabilizes operation, the middle layer rejects disturbances, and the top layer is used to ensure reliable operation. Three degrees of freedom are available to achieve this: the pressure drop over the CCV, $u$, the blade tip speed, $U$, and the flow through the compressor, $\phi_0$, as determined by the throttle. The three layers are described in more detail in the following subsections.

### *3.1. Stabilizing control layer*

The purpose of the lowest control layer is to stabilize the compressor beyond the surge line. For this purpose, we use a feedback linearizing controller which adjusts the CCV. Feedback linearizing control enables controlling non-linear systems with a linear control law, allowing for higher sampling frequencies due to the reduced computational complexity. Since the surge phenomenon happens on a short time scale, while simultaneously being non-linear, the use of feedback linearization is appropriate. We use the feedback linearizing controller presented by Backi et al. (2016). A full description and derivation of the control law is given there.

The proposed feedback linearizing controller for the CCV is:

$$u = \mu_1\hat{\phi} + \mu_2\hat{\psi}, \tag{6}$$

where $u$ is the pressure drop across the CCV and $\mu_1$ and $\mu_2$ are controller tuning parameters.

*3.2. Supervisory control layer (Local disturbance rejection: Self-optimizing control)*

After stabilizing the system with the CCV, we can optimize operation by adjusting the flow through the system. The operational objective is to maximize the compressor efficiency, but operation too close to the surge point is penalized.

$$\min_{\phi_0, U} \quad J^{SOC} = -\eta(\phi_0) + \beta(2W - \phi_0). \tag{7}$$

In the above expression $\eta$ is the efficiency and $\beta$ is the penalty weight. Using self-optimizing control (Skogestad, 2000; Jäschke et al., 2017), we can keep the operation such that it is near optimal in the sense of (7) by controlling a combination of carefully chosen plant measurements $y$, to a predetermined set-point:

$$c = H^{SOC} y \tag{8}$$

In this case, the plant measurements are augmented by disturbance measurements, $d = \begin{bmatrix} W & H & \psi_{C_0} \end{bmatrix}^\mathsf{T}$, such that $y = \begin{bmatrix} \phi & \psi & d \end{bmatrix}^\mathsf{T}$. A measurement combination matrix $H^{SOC}$ that can be shown to minimize the average loss $L = J(\phi_0, d) - J^{opt}\left(\phi_0^{opt}, d\right)$ is (Yelchuru and Skogestad, 2010)

$$\left(H^{SOC}\right)^\mathsf{T} = (YY^\mathsf{T})^{-1} G^y, \tag{9}$$

where

$$Y = \left[FW_d \quad W_{n^y}\right], \tag{10}$$

and $G^y = \left.\frac{\partial y}{\partial \phi_0}\right|_{\phi_0^{nom}}$ is the linearized system model evaluated at the nominal operating point, $F = \frac{dy^{opt}}{dd}$ is the optimal sensitivity matrix, and $W_{n^y}$ and $W_d$ are diagonal matrices of appropriate sizes with the variances of the measurement errors / noise $n^y$ and the variances of $d$.

*3.3. Optimal economic and reliable operation*

In the top control layer, we devise a dynamic real-time optimization (DRTO) scheme to calculate the optimal compressor speed $U$ and penalty weight $\beta$ for the SOC layer. The purpose of this layer is to adjust operation for the other layers to ensure both economic optimality and satisfaction of operational and reliability constraints. At each time step we solve the following dynamic optimization problem

$$\min_{\beta, U} \quad J^{DRTO} = -\int_0^{t_f} NPV(\phi_0)dt = -\int_0^{t_f} \frac{\phi_0}{(1+i)^t} dt \tag{11}$$

$$s.t. \quad x < x_{max} \tag{12}$$

$$\psi_{out} > \psi_{out,min}, \tag{13}$$

where $NPV$ signifies the net present value with discount rate $i$ and $x$ is the degradation from (5). $\psi_{out} = \hat{\psi} + \psi_{res}$ is the outlet pressure from the compressor.

## 4. Simulations

The system described in Section 2 and the control structure described in Section 3, are implemented in MATLAB/Simulink and Casadi 3.0.0 (Andersson, 2013). IPOPT 3.12.3 (Wächter and Biegler, 2006) is used to solve the optimization problems (7) and (11).

*4.1. Stabilizing control*

Figure 4 shows the response of the system with the surge controller turned off (solid blue line) and with the surge controller turned on (dashed blue line) to a step change in $\phi_0$. After the step, the new set-point lies within the unstable operating region, causing the limit cycle behavior in the uncontrolled case.

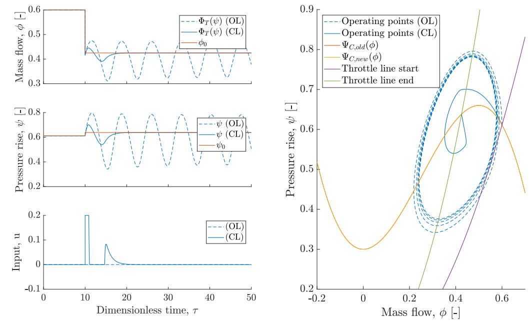


Figure 4: Closed-loop (CL) and open-loop (OL) responses to a set-point change in $\phi_0$ into the unstable region.

### *4.2. Local disturbance rejection (Self-optimizing control)*

Fig. 5 shows the response of the SOC structure (open loop (OL) and closed loop (CL)). As can be seen, the CL structure drives operation back to the optimal point. The OL structure, while stable thanks to the surge controller, does not. Operation continues at a sub-optimal operating point, resulting in higher cost. Note that for the simulated disturbance in $H$ and $\psi_{c_0}$, the steady state loss for the CL structure is higher than that of the OL structure. On the other hand, a step in $W$ results in a lower loss, illustrating that it is the average loss that is minimized by (9), not the loss for each individual disturbance.

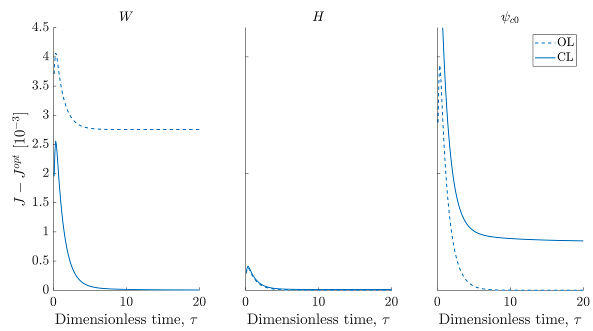


Figure 5: Open loop (OL) and closed loop (CL) losses for the SOC structure for the disturbances $W$, $H$ and $\phi_{c_0}$

### *4.3. Optimal economic and reliable operation*

We consider three cases of DRTO. The DRTO1 and DRTO2 do not take the degratation constraint into account, and differ in terms of the maximum allowable shaft speed. DRTO1 allows higher shaft speed. DRTO2 is more conservative with a lower maximum allowable shaft speed. The DRTO3 is health-aware and does not have constraints on the shaft speed, but instead ensures that the degradation is not exceeded. The closed-loop responses of the DRTOs are shown in Fig. 6. It can be seen that operation is adjusted to maximize the NPV of the production in all three cases by gradually reducing the production over time. However, only the ”conservative” DRTO2 with the lower maximum allowable speed and the health aware DRTO structures satisfy the reliability constraints. The non-health-aware DRTOs do not ”see” the compressor degradation. The system is disturbed at around $t = 1.5$ and again at $t = 2.5$, by stepping first up, then down in the degradation speed, to show that the health-aware control structure takes into account the updated health information.

## 5. Concluding remarks and future work

We have proposed a control structure for a compression system subject to long-term load-induced degradation. By using time scale separation it is possible to counteract surge and reject disturbances, while also achieving long term optimality and satisfaction of reliability constraints. We have shown that the proposed method is better than a ”regular” DRTO scheme, in which reliability considerations are not taken into account when planning future production.

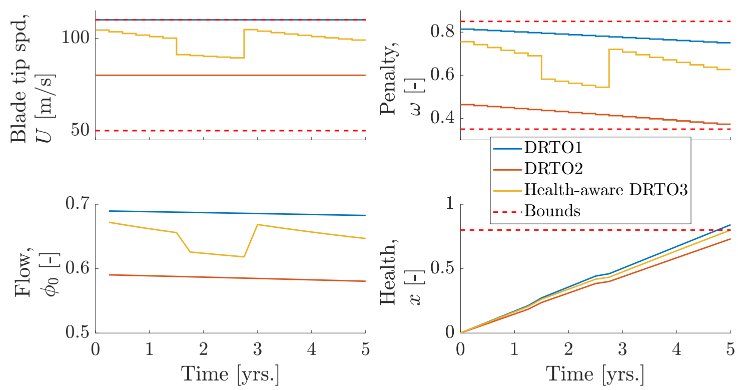


Figure 6: Closed loop responses of the regular DRTOs and the health-aware DRTO to disturbances in degradation speed.

Several assumptions have been made in this work: we assume perfect state feedback for the DRTO, meaning that we can measure the health indicator state directly and without errors. This is somewhat unrealistic. In practice, we need to estimate the health indicator from other measurements. In the DRTO, we did not use parameter estimation to adapt the model when the operating conditions changed. Finally, the DRTO has to be made robust towards model uncertainty by formulating a robust/stochastic optimization problem. This will be addressed in future work.

## 6. Acknowledgments

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