HEALTH-AWARE OPERATION OF A SUBSEA GAS COMPRESSION SYSTEM UNDER UNCERTAINTY

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Abstract

In this paper we apply health-aware control ideas to the optimal operation of a subsea gas compression plant. Subsea systems operate in harsh environments and under uncertain and varying operation conditions. Because they are very difficult and expensive to access, an optimal operational strategy that tries to maximize hydrocarbon production must ensure that no unplanned shutdowns due to premature equipment failures occur. In this paper we apply two approaches for optimization under uncertainty in order to maximize the economic profit, while ensuring that the subsea compression plant remains operational until the next planned maintenance. We consider a min-max robust optimization and a scenario-based optimization with recourse. Although both methods avoid unplanned shutdowns, the scenario-based method results in a less conservative solution at the cost of a larger problem size.

Keywords

Health-aware control, model predictive control, optimization under uncertainty

Introduction

Most oil and gas fields that are easy to develop have been exhausted, forcing the petroleum industry to produce from more difficult fields with larger water depths, longer tie-back distances and harsh climate conditions. Subsea processing technology is an enabling technology for development of such fields, although several new challenges arise when production and processing facilities are put on the seabed (Ramberg et al., 2013). One of the challenges is that the process is not easily accessible for maintenance. Since maintenance interventions require specialized lifting vessels, fair weather conditions and available spare modules, unanticipated breakdowns can lead to long production halts and large production losses. The lifting vessels sometimes cost several tens to hundreds of millions of dollars to rent, and must be booked several months in advance. For this reason, stringent requirements on safety and reliability are imposed on operation of these processes. This in turn often leads to conservative design and operation strategies and the economic potential of the field is often not fully realized.

In this paper, we propose to combine reliability and operational considerations in an model predictive control-like framework with shrinking horizon. In particular, we present an approach that ensures that the remaining useful life (RUL) of the equipment is not exhausted before the next planned maintenance stop, while at the same time maximizing the expected operational profit.

A few other authors investigated the combination of the prognostics and health monitoring (PHM) with advanced control methods such as model predictive control (MPC). MPC is a control strategy based on repeated optimization of a process model to obtain optimal input trajectories. Due to its ability to deal with multi-variate, constrained problems, MPC has gained popularity in industry in recent years (Morari and Lee, 1999). Health prognostics information is usually not taken explicitly into consideration when calculating the optimal control moves, and this can lead to sub-optimal operation (Salazar et al., 2016). If a prognostic model is available,

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the system health state can be included as constraints in the optimization (Pereira et al., 2010; Salazar et al., 2016), or as terms in the objective function (Escobet et al., 2012). The term *health-aware control* was introduced by Escobet et al. (2012) to describe a control structure that pro-actively adjusts the inputs to prevent a fault from occurring. The health-aware control structure thereby distinguishes itself from the more established fault-tolerant control (FTC) structure, which only takes corrective action once a fault has already occurred. Similar ideas are discussed in papers by Pereira et al. (2010), who include PHM in an MPC framework to redistribute the control efforts among redundant actuators to prevent actuator breakdown, and Salazar et al. (2016), who model the reliability of pumps in a drinking water network using Bayesian networks and include the system reliability in the MPC formulation.

In this work we present a comparative study of two robust approaches applied to a subsea gas compression system. We model a subsea gas compression station and define the optimal control objective. The reliability of the system is ensured by constraining the health-state of the compressor, which is assumed to be the critical component. The degradation of the compressor health is assumed to be a function of the input usage and uncertain parameters. In particular, we assume parametric uncertainty in the compressor health degradation model and calculate the robust solution using both a scenario-based MPC approach, and a worst-case MPC approach.

Combining Prognostics and Control

To start with, we assume that the health state, h, of the system is observable, and we define a minimum health limit, h_{min}, above which we have to operate. Violation of this constraint corresponds to an unacceptable risk of failure. We assume the health to be monotonously decreasing, i.e. the system is not repaired or maintained before the final time t_f is reached. Because of the fixed final time, the MPC has a shrinking horizon rather than the more common receding horizon.

Due to the inherent uncertainty in the model, the optimization problem solved at each time step in the MPC is usually stochastic, because most prognostic models are statistics-based. The stochastic optimization problem can be written as

$$\min_{\mathbf{u}} \quad \mathbb{E}(f_0(\mathbf{u},\mathbf{p})) \quad \text{s.t.} \begin{cases} g_i(\mathbf{u},\mathbf{p}) = 0 & {\scriptstyle i=1,\dots,n_g} \\ f_j(\mathbf{u},\mathbf{p}) \geq 0 & {\scriptstyle j=1,\dots,n_f} \\ h_k(\mathbf{u},\mathbf{p}) \geq 0 & {\scriptstyle k=1,\dots,n_h} \end{cases} \tag{1}$$

where $\mathbf{p} \in \mathcal{P}$. In the above expression, we use $\mathbf{u}$ to denote the inputs and $\mathbf{p}$ to denote the uncertain parameters, which are contained in the (bounded) set $\mathcal{P}$. f_0 is the objective function, g are the equality constraints, f are the inequality constraints and h are the constraints on the equipment RUL. The operator $\mathbb{E}$ is used to signify the expected value of the objective function. Below, we discuss two approaches for addressing the uncertainty.

Min-Max Model Predictive Control

One way to handle the uncertainty is the "min-max"-approach, in which the objective function is optimized given a worst-case realization of the uncertain parameters. The min-max-approach, sometimes also referred to as the "robust" approach, was implemented in a receding horizon MPC framework in Zheng and Morari (1993).

In the non-linear case, identifying the worst-case realization can usually not be done explicitly. Rather, the worst-case realization is found through maximization of the inequality constraints, subject to bounds on the norm of the random parameters. Consequently, a bi-level optimization problem has to be solved at each stage of the min-max MPC.

$$\min_{\mathbf{u}} \quad \mathbb{E}(f_0(\mathbf{u},\mathbf{p})) \quad \text{s.t.} \begin{cases} \phi_i(\mathbf{u}) \geq 0 & {\scriptstyle i=1,\dots,n_f+n_h} \end{cases} \tag{2a}$$

where

$$\phi_i(\mathbf{u}) = \max_{\mathbf{p}} \quad \hat{f}_i(\mathbf{u},\mathbf{p}) \quad \text{s.t.} \begin{cases} g_j(\mathbf{u},\mathbf{p}) = 0 & {\scriptstyle j=1,\dots,n_g} \\ \mathbf{p} \in \mathcal{P} \end{cases} \tag{2b}$$

and $\hat{f} = \left[f_1, \dots, f_{n_f}, h_1, \dots, h_{n_h}\right]^\intercal$. Bi-level problems are difficult to solve, as they quickly become numerically intractable. Diehl et al. (2006) propose an approximated robust counterpart of the nonlinear optimization problem, which is numerically efficient. The min-max-approach is often very conservative (Scokaert and Mayne, 1998), because the possibility of future information about the realizations, i.e. feedback, and the possibility of other realizations than the worst-case, are ignored when solving the problem.

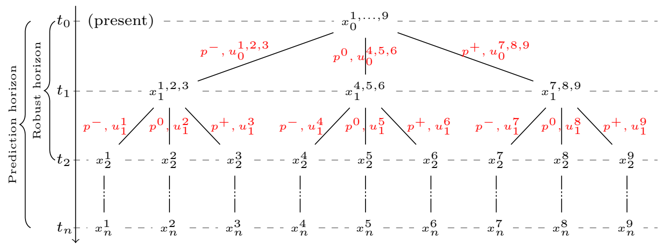

Figure 1. Illustration of a scenario tree with robust horizon of length $n_{robust} = 2$ and prediction horizon of length n. At each stage there are three possible realizations of the uncertain parameter, p^+, p^0 and p^-.

Scenario-based Model Predictive Control

As a remedy, Scokaert and Mayne (1998) propose a multi-stage approach with recourse. Scenario-based MPC has its roots in multi-stage stochastic programming. The core idea in scenario-based optimization is to assume a discrete probability distribution for the uncertain parameters. A finite number of scenarios are then generated to represent how the uncertainty may develop over time. For the resulting scenario tree, the expected objective function value is then minimized subject to non-anticipativity constraints, which require that the decisions only depend on the past realizations of the random parameters and their probability distribution. Future realizations can not be anticipated, and are therefore not included in the decision making process (Dupačová et al., 2000).

Due to the need for additional variables and constraints, the complexity of scenario-based MPC increases with the number of scenarios. In order to keep the problem tractable, the scenario tree only branches up until a certain stage, called the robust horizon (Lucia et al., 2013). After the robust horizon, the realizations of the uncertain parameters are kept constant.

An illustration of a scenario tree with a robust horizon with length $n_{robust} = 2$ and a prediction horizon with length n is shown in Fig. 1.

A challenging task is the selection of a representative scenario tree. Especially when the dimensionality of the problem becomes large, it is nontrivial to reduce the scenario tree to a manageable size. One way to generate the scenario tree by using combinations of the maximum, minimum and nominal uncertain parameters. A scenario tree generated this way will result in a feasible solution for linear systems, and typically works for non-linear systems in which the degree of non-linearity is not too large (Lucia et al., 2013).

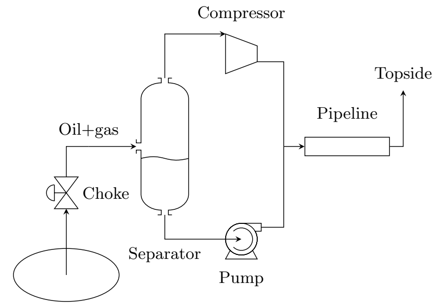

Figure 2. Process diagram of the subsea gas compression station.

Case study

Process description

A subsea gas compression station (Fig. 2) is used to illustrate the robust health-aware control strategy in this paper. The process is similar to the gas compression stations installed on the Åsgard field and the Ormen Lange pilot.

The plant consists of a single choke, which regulates the flow of oil and gas from the reservoir, a scrubber which separates the gas from the oil, and a wet-gas compressor to achieve sufficient gas pressure for transport through the pipeline. Due to non-perfect separation, some liquid droplets are carried over in the gas stream. The separation efficiency of the scrubber is assumed to be a function of the gas velocity and the fluid density (Austrheim, 2006). The compressor in our system is a wet gas compressor which can handle moderate liquid carry-over, with a suction gas-volume-fraction from 0.95 to 1. A full description of the compressor model, including the compressor maps, can be found in Aguilera (2013). The liquid stream from the separator is boosted before being recombined with the compressed gas stream. Finally, the multiphase flow is sent to the receiving facility through a long subsea pipeline.

We assume that the wet-gas compressor is the critical component in terms of overall system reliability. We therefore make the simplifying assumption that the wet-gas compressor is the only component whose reliability will decrease on the given time horizon. As rotating equipment is prone to wear damage, leakage and signal failure, due to its complexity and many moving parts (Liu, 2015), this assumption seems reasonable. Tests from the Ormen Lange pilot have shown that the RUL of the compressor is strongly linked to the operating conditions (Eriksson et al., 2014), which makes it a good choice for showcasing a health-aware operating strategy.

Modeling the compressor degradation

In general it is hard to predict exactly when or how a compressor is going to fail. Liu (2015) lists some common causes for compressor failure, including how they can be monitored. Both Eriksson et al. (2014) and Liu (2015) report that the magnetic bearings of the compressor are critical components and prone to fatigue failure. Eriksson et al. (2014) also found that the health state of the active magnetic bearings is observable through their power consumption. The reason for this is that damage to the compressor innards causes an imbalance of the driving shaft. Consequently the magnetic bearings require more power to stabilize this imbalance.

We propose to model the health degradation of the compressor over one month of operation, Δh, as a result of wear, which is proportional to the dimensionless compressor speed N, and shock damage, which is caused by set-point changes in the compressor speed, $|\Delta N|$.

$$\Delta h = -\left(\underbrace{p_N N^n}_{\text{Wear and tear}} + \underbrace{p_\Delta |\Delta N|^{n_\Delta}}_{\text{Shock damage}} \right) \cdot f(\mathbf{y}) \tag{3}$$

Here, h is the compressor health, which ranges from 1 to 0 (breakdown). $\mathbf{p} = [p_N p_\Delta]$ denotes the random parameters that affect the degradation. We assume that $\mathbf{p}$ follows a Gaussian distribution. The function f, which is a function of the measurements $\mathbf{y}$, is introduced to take into account the increased rate of wear in multiphase fluids. Eriksson et al. (2014) report that the compressor life scales cubically with the compressor speed. We therefore chose the coefficients $n = n_\Delta = 3$. Furthermore we assume that the compressor degrades exponentially with the liquid content in the gas.

$$\Delta h = -\left(p_N N^3 + p_\Delta |\Delta N|^3\right) \cdot \exp(1 - \text{GVF}) \tag{4}$$

where GVF is the gas volume fraction at the inlet of the compressor.

Since p_N, N, p_Δ and $|\Delta N|$are nonnegative, the compressor health is monotonously decreasing, and failure is defined as the event when h goes below a failure threshold value h_{min}. We assume that h is measurable.

Defining Optimal Control Problems

The objective of the plant operation is to maximize the profit of the plant between *planned* maintenance stops. As a simplification, we assume that the variation in the variable operational expenses (in particular the power usage of the compressor) are negligible compared to the income due to gas production. Furthermore, we assume that gas is the only valuable product, and the contribution of oil can be neglected in the objective function. Taken into account that gas that is produced today, is worth more than gas that is produced in the future, we use the net present value (NPV) of the gas in the objective function.

Table 1. Bounds for the variables

Variable	Lower	Upper
Discharge pressure	15 bar	-
Compressor health	0.8	1.0
Compressor surge	0	-
Compressor choke	0	-
Compressor speed	0.6	1.05
Choke opening	0.0	1.0

The discharge pressure from the compressor is bounded from below to make sure that the carbohydrate stream has enough pressure to overcome the flow resistance in the transport pipeline. Moreover, we add constraints to prevent compressor surge and compressor choke/Stonewall conditions. Both these phenomena are undesired, so this operating region must be avoided. All bounds are listed in Tab. 1.

Deterministic formulation

We formulate the objective function for the optimal control problem as

$$f_0(\dot{m}_{gas}, t_f) = -\int_0^{t_f} \text{NPV}(\dot{m}_{gas}) dt, \tag{5}$$

where t_f is the time until the next planned maintenance stop.

The optimization problem is solved using Casadi 3.0.0 (Andersson, 2013) in MATLAB R2015a. The problem is discretized using a third order direct collocation scheme and solved with Ipopt 3.12.3 (Wächter and Biegler, 2006).

Stochastic multi-stage approach

Robustness towards parametric uncertainty in the parameters p_N and $p_{\Delta N}$ in the compressor degradation model from Eq. (3) is achieved by discretizing their probability density function and applying the scenario-based method. Five different scenarios are considered: *HH*, *HL*, *LH*, *LL* and *mean*. These are the combinations of the maximum, minimum and nominal realizations.

Table 2. Values of the uncertain variables p_N and $p_{\Delta N}$ in the scenarios used to generate the scenario tree.

Scenario	p_N	$p_{\Delta N}$
LL	0.006 $(\mu - 2\sigma)$	0.6 $(\mu - 2\sigma)$
LH	0.006 $(\mu - 2\sigma)$	1.8 $(\mu + 2\sigma)$
HL	0.018 $(\mu + 2\sigma)$	0.6 $(\mu - 2\sigma)$
HH	0.018 $(\mu + 2\sigma)$	1.8 $(\mu + 2\sigma)$
mean	0.012 (μ)	1.2 (μ)

See Tab. 2 for the specific values. All five scenarios are equally probable. An initial prediction horizon of length $n = 20$ and a robust horizon of length $n_{robust} = 1$ is used to speed up the calculation. Higher robust horizons were tested as well, but were not found to improve the solution significantly while resulting in a much higher computational cost.

Min-max approach

Robustness can also be achieved by considering a worst-case scenario in the optimization. For a general, non-linear case, the approximate robust counterpart problem may be solved using the method described in Diehl et al. (2006). For the current system, it is not strictly necessary to define the robust counterpart, as it can be determined a priori that the *HH*-scenario from Tab. 2 will always be the worst-case scenario.

Results

Deterministic open-loop solution

The deterministic open-loop solution can be seen in Fig. 3. It can be seen that the constraints are satisfied, and that the compressor health constraint is active at the end of the horizon. Since the NPV of the gas production is considered, early production is favored over late production.

Closed-loop results

The closed-loop responses of three control structures are shown in Figure 4. Firstly, notice that the non-robust approach, in which expected values are considered for the uncertain parameters, leads to repeated violations of the constraints on the discharge pressure and the final health constraint. In contrast, the two robust approaches both satisfy all constraints, as is to be expected. In both cases, there is a back-off from the con-

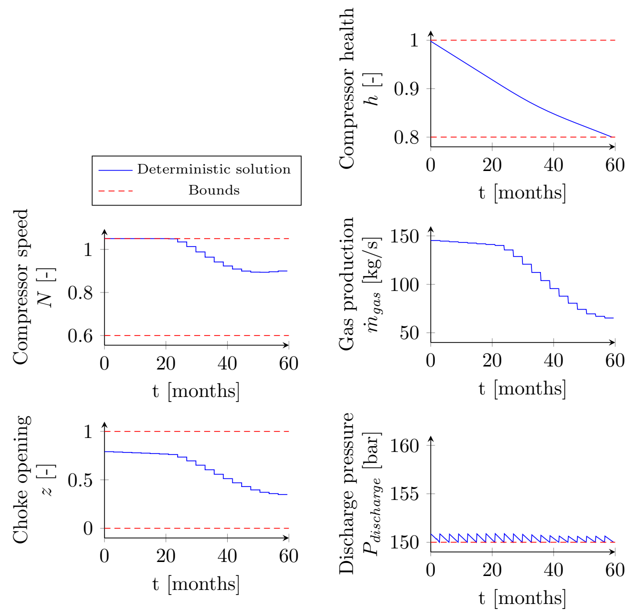

Figure 3. Deterministic open-loop solution when $p_N = 0.015$ and $p_\Delta = 1.5$.

Table 3. Normalized profit, i.e. net present gas production, for the three methods (in closed-loop).

Method	**Discounted closed-loop profit**
Scenario-based	1.026
Worst-case	1.000
Nominal case	1.056*

* Constraint violation

straints to account for uncertainty. It can be seen that the scenario-based approach is less conservative than the worst-case approach, since it results in overall higher gas production, $\dot{m}_{gas}$.

The values of the cost function for the three different cases are shown in Tab. 3. Note that the scenario-based method yields a higher net present gas production than the worst-case method, but lower than the non-robust method based on expected values. The higher gas production for the non-robust case comes at the cost of constraint violation (i.e. an unplanned maintenance stop). The 2.6% higher net present gas production of the scenario-based method, compared to the worst-case approach, may be a substantial increase in profit.

Conclusion

We have developed a model for a subsea gas compression system and shown how prognostics can be included in the decision-making process to obtain a con-

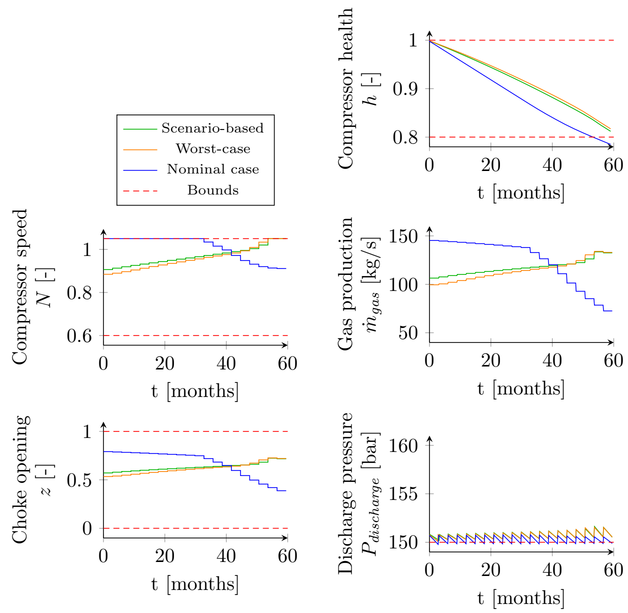

Figure 4. Comparison of closed-loop performance of three different controllers in the presence of uncertainty. The realizations of the uncertain variables are $p_N = 0.015$ *and* $p_\Delta = 1.5$.

trol structure that gives economical and safe operation. Robustness towards parametric uncertainty is very important in this application, since the health-constraint always will be active. To achieve robustness, we employ a scenario-based optimization method, which is shown to be less conservative than a worst-case approach.

Future work will focus on measurement feedback and health state estimation, more detailed degradation models and extension to system-wide health-aware operation.

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