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Integration of time scales in health-aware control ★

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Abstract: Health-aware control (HAC) consists of computing the control action considering the degradation state of the plant components. The equipment degradation typically happens on a slower time scale, while the control and optimization of the economic performance on a much faster time scale. As such, HAC leads to a hierarchical control structure based on time-scale separation. We explore the different layers of this problem using a gas-lift network with choke valve degradation as an example. The main contributions of this work are to propose a new HAC system hierarchy and to show how regulatory layers can also reduce equipment degradation.

Keywords: Process control, Maintenance, Optimization, Subsea processes.

1. INTRODUCTION

Health-aware control (HAC) takes into account traditional control objectives as well as the current and future (prognostic) condition of the equipment in the plant to compute the next control action (Escobet et al., 2012). The idea is to find the best trade-off between economic performance and extending the equipment's remaining useful life (RUL). HAC is essential in situations where the maintenance is complex and costly (e.g., subsea operation (Verheyleweghen et al., 2018; Verheyleweghen and Jäschke, 2018; Matias et al., 2020)), the process safety depends on the condition of the equipment (e.g., pasteurization plant (Pour et al., 2018)) or in cases where the RUL can be significantly extended (e.g., batteries (Lucia et al., 2017)).

Control systems are usually decomposed in time-scales layers (Seborg et al., 2010). The slower upper layers control inputs that are important on a long time scale and then send a setpoint to the faster lower layers that also take care of fast disturbances. In the HAC, equipment degradation is usually slow and can happen over a scale of years. Also, degradation measurements are not frequently available (DNV, 2015). On the other hand, economic optimization can be performed on a scale of hours/minutes while the disturbance rejection can be on a scale of days/minutes/seconds (Seborg et al., 2010). Therefore, the HAC strategy needs to optimize the process on a short time scale and guarantee the process's safety in the long run.

In literature, several control structure (strategy) designs have been proposed for HAC. Verheyleweghen and Jäschke (2018) proposed a single-layer Health-aware Real-Time Optimization (HRTO) in a shrinking horizon. A steady-state process model was combined with a dynamic degradation model, and a maximum degradation constraint was used to enforce equipment safety. Matias et al. (2020) similarly formulated the problem using a single-layer Health-aware Economic Model Predictive Control (HEMPC) with a receding horizon. Bernardino et al. (2020) also applied a single-layer scheme for a setpoint tracking MPC with an RUL term in the objective function. Verheyleweghen et al. (2018) proposed a three-layer structure with an HRTO in the upper level and a self-optimizing control below. Pour et al. (2018) compared a single-layer HMPC with a two-layer HMPC/MPC strategy. The upper HMPC layer sends a setpoint for a regulatory MPC layer on the two-layer scheme. The authors concluded that the multi-layer allowed a better economic performance for the same degradation level reduction. Finally, Verheyleweghen (2020) developed a two-layer strategy where an HRTO sends a setpoint for the degradation rate to a HEMPC. Combining maintenance and production scheduling has also been suggested (Verheyleweghen, 2020).

All the single-layer HAC presented the same drawbacks because they need to solve the optimization related to the long-run RUL problem often, and computing the optimal control problem solution is often impossible in practice because of the long horizon required for the degradation prognostic. Furthermore, the degradation models increase the dimension of the problem to be solved, and the trade-off between health and economics can be challenging to formulate in a single optimization problem.

The multi-layer scheme is a more natural choice for a control structure that takes both degradation and control into account. In this work, we investigate the connection of the control layers in a HAC. We propose a dedicated control structure for the HAC, consisting of an HRTO in the upper layer and an EMPC with a Proportional-Integral controller model (PI EMPC) at the lower layer. This strategy has the advantage that no trade-off between production and extending the RUL of the equipment is considered in the lower layers. The goal of the HRTO is to ensure that the different equipment components degrade coordinated and in such a way that it contributes

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to the overall economic performance of the process. For example, this could mean ensuring that all the equipment will be as equally degraded as much as possible safely for the subsequent maintenance intervention. The PI EMPC layer below only focuses on rejecting disturbance and optimizing the economic performance of the process on a fast timescale. This feature distinguishes our methodology from the one proposed by Verheyleweghen (2020), where the prognostic model is used in both layers, making the problem harder to solve and imposing the profit health trade-off on the fast time scale. Furthermore, in our approach, the PI controller model was included in the controller. As pointed out recently (Kumar et al., 2023) the PI EMPC has better constraint-handling skills and economic performance in the face of unmeasured disturbances.

1.1 Paper structure and main contributions

The main contributions of this work are to propose a new HAC system hierarchy and to show how regulatory layers can also reduce equipment degradation. We demonstrate and evaluate the control structure on a gas-lift well network with choke valve erosion caused by sand particles. The simulation results provide valuable insights into the importance of the multi-layer HAC strategy in preventing equipment breakdown. The remainder of the paper is structured as follows: Section 2 briefly presents our hierarchical HAC strategy; Section 3 presents the gas-lift oil well network case study; Section 4 the simulation setup; Section 5 present the simulated results; Section 6 the discussion and section 7 the work conclusions.

2. MULTI-LAYER CONTROL STRUCTURE FOR HEALTH-AWARE OPERATION

Figure 1 illustrates the proposed multi-layer hierarchical control structure. On the top is the HRTO layer feed with the degradation level estimation from the plant and the information about the next planned maintenance. The HRTO problem is solved in a shrinking horizon. The problem determines the constraints that the operation must obey during the functioning, such that the next planned maintenance can be reached safely, without too much production loss due to conservative operations. The health constraint is sent to the lower layer, this constraint can change from case to case but typically is an upper bound on a manipulated variable related to the equipment degradation. PI EMPC obtained the states estimated from the plant and the health constraint from the HRTO layer and solved the problem in a receding horizon manner. The PI EMPC layer has no degradation model; its only goal is maximizing profit subjected to the health constraint. The manipulated variables of the PI EMPC may differ from the ones in the HRTO layer, however, in the case study used in this work, they are the same. In the following subsections, the mathematical formulation of each layer is presented.

2.1 Health-aware Real-time Optimization (HRTO)

The HRTO layer optimizes the process on a long timescale while ensuring the equipment will not break down until the next planned maintenance stop. Since the equipment

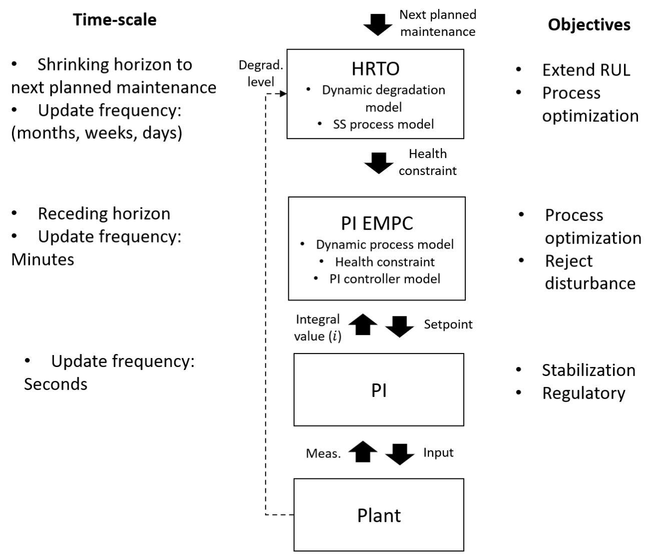

Fig. 1. Proposed control system hierarchy.

degradation is typically much slower than the process dynamics, a steady-state model ($f(\cdot)$) is used for the process, and a dynamic model for the degradation process $d = g(\cdot)$. The discrete version of the HRTO can be formulated as follows:

$$\begin{aligned} \max_{x,u} \quad & \sum_{k=0}^{n_{ph}-1} P_k \\ \text{s.t.} \quad & 0 = f(x_k, u_k) \\ & d_{k+1} = g(d_k, x_k, u_k) \\ & d_k \leq d_{max} \end{aligned} \tag{1}$$

in which k represents the k^{th} sampling time and n_{ph} the HRTO prediction horizon (i.e., the next planned maintenance intervention). The manipulated input sequence $u = [u_0, ..., u_{n_{ch}}]$, where $u_{n_{ch}}$ is the HRTO control horizon. x_k are the states of the systems at the sampling time k. The objective function is the summation of the operational profit (P_k) of the system in each sample time. The variable d_k refers to the degradation states of the equipment at sample time k, and d_{max} is the maximum acceptable equipment degradation before the next planned maintenance intervention, usually set to a value near the experimentally determined equipment breakdown limit. The optimization problem (1) is solved in a shrinking horizon at a much slower frequency than the plant measurement frequency, usually days. After the optimization problem has been solved, only the first control action (u_0) is sent to the PI EMPC layer below which will be used as a health constraint to the equipment.

2.2 PI Economic Model Predictive Control (PI EMPC)

The goal of this layer is to maximize the system's profit and reject fast disturbances while keeping all the inputs within the health bounds set by the upper layer.

$$
\begin{aligned}
\max_{x,u} \quad & \sum_{k=0}^{n_{pe}-1} \alpha \cdot P_k - \beta \cdot s_k - 1/2 \Delta u_k^T Q_u \Delta u_k \\
\text{s.t.} \quad & x_{k+1} = f(x_k, u_k) \\
& u_k \leq u_{max}^{HRTO} + s_k \\
& u_k^{total} \leq u_{max}^{total} \\
& \Delta u_k \leq \Delta u_{max} \\
& h_{PI}(x_k, u_k, i_k, y_k^{pi}, u_k^{pi}) = 0
\end{aligned} \tag{2}
$$

in which n_{pe} the PI MPC prediction horizon. u is the manipulated input sequence $u = [u_0, ..., u_{n_{ce}}]$, where $u_{n_{ce}}$ is the PI EMPC control horizon, $\Delta u_k = u_{k+1} - u_k$ and $u_k^{total} = \sum u_k$. The weighting factor at the objective function for the process $profit$, slack variables and input penalization are α, β and Q_u, respectively. The variable u_{max}^{HRTO} is the optimal solution from the HRTO layer that is sent as a health constraint on the manipulated variable of the PI MPC optimization problem. To avoid control problem infeasibility, slack variables are introduced on the health constraints. Finally, $h_{PI}(\cdot)$ is the Proportional-Integral (PI) controller model that will be described below (Equations 3, 4 and 5). This optimization problem is solved with a fixed receding horizon at a faster frequency than the HRTO problem, usually in minutes. Only the first control action is sent as a setpoint for the PI controller.

PI controller model: PI/PID is usually kept aside from the health-aware control studies. Despite that, the lower layers can significantly impact valve degradation, for example, by decreasing input usage using dead zones. However, here we are not going to discuss the potential contributions of PI controllers, but instead, how the integration with EMPC can potentially improve the controller performance. The formulation of the PI EMPC follows recent results that highlighted the advantages of that formulation (Kumar et al., 2023). There, the authors showed that including PI controllers inside the MPC controller can improve the constraint handling, which is a good fit in our formulation since the systematic violation of the u_{max}^{HRTO} constraint can lead to faster degradation of the equipment. Furthermore, it highlights the potential of PI EMPC to increase profit in the presence of unmeasured disturbances compared to the standard EMPC. In that way, the implementation of the PI EMPC will follow the formulation presented in Kumar et al. (2023). A discrete-time first-order model of the PI feedback loop to describe the effect of a setpoint change (u^{sp}) into the measure variable (y) was considered:

$$
y_{k+1} = y_k(1 - \frac{\Delta t}{\tau_{cl}}) + \frac{K_{cl}}{\tau_{cl}} \Delta t \ u_k^{sp} \tag{3}
$$

in which K_{cl} and τ_{cl} are the gain and time constant parameters and Δt is the plant measurement sampling time. The discrete-time linear model of the PI controller was used in the PI EMPC:

$$
\begin{aligned}
u_{k+1}^{pi} &= u_k^{pi} + K(y_k^{sp} - y_k) + \frac{K}{\tau_I} i_k \\
i_{k+1} &= i_k + \Delta t(y_k^{sp} - y_k)
\end{aligned} \tag{4}
$$

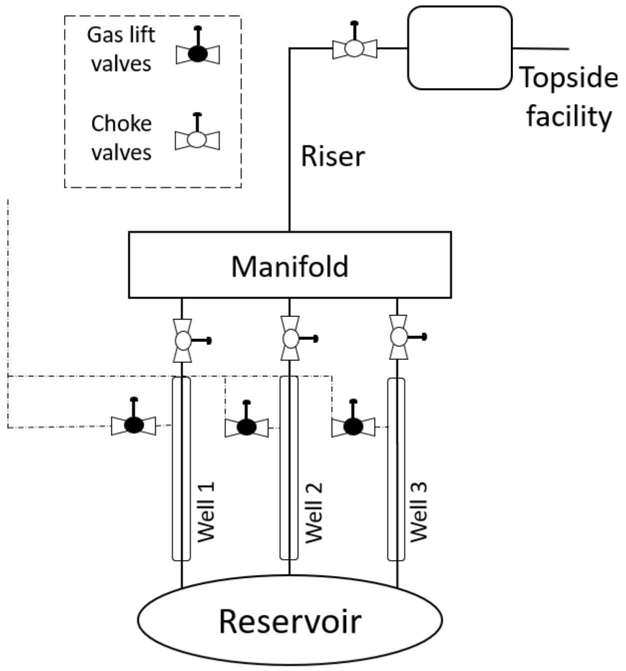

Fig. 2. Illustration of the oil and gas network with artificial gas-lift.

in which K and τ_I are the PI tuning parameters and u_k^{pi} is the actuator position computed by the PI controller. The variable i is the PI controller integral value that is assumed to be known by the PI EMPC controller (Figure 1), as well as the PI tuning parameters. Constraints on the actuator are also imposed as follows:

$$
u_{min}^{pi} \leq u_k^{pi} \leq u_{max}^{pi} \tag{5}
$$

3. CASE STUDY: GAS-LIFT OIL WELL NETWORK

The HAC strategy presented above is evaluated on a gas-lift oil well network. The system is illustrated in Figure 2, the main idea is to increase oil production in the top facility by injecting gas into the wells through the gas lift valves. Because of the presence of sand particles in the reservoir, erosion is prone to happen on the production choke valves in the wells, which aim to control production and avoid any pressure fluctuation. The erosion of the choke valves is proportional to the flow rate on the valves (DNV, 2015), which in turn is controlled by the gas-lift rate. HAC strategies have been proposed for that system by splitting the gas-lift rate among the wells considering the different levels of erosion of each valve (Verheyleweghen et al., 2018; Matias et al., 2020).

3.1 Gas-lift model

The model to describe the gas-lift well system is based on the work of Krishnamoorthy et al. (2016). The mass balances in each well are:

$$
\begin{aligned}
\dot{m}_{gt} &= w_{lg} + w_{rg} - w_{pg} \\
\dot{m}_{ot} &= w_{ro} - w_{po}
\end{aligned} \tag{6}
$$

w_{lg} is the gas-lift gas mass flow rates, w_{rg} and w_{ro} are the gas and oil mass flow rates from the reservoir, and w_{pg} and w_{po} are the gas and oil mass flow rates of the produced gas and oil. m_{gt} and m_{ot} are the gas and oil mass holdup in the well. The gas-lift rate (w_{lg}) and the total flow at the top facility (w_t) can be adjusted by opening and closing the valves. The valve equations then describe the flow rate:

$$\begin{aligned} w_t &= Z_t C_{pc} \sqrt{\rho_w (p_{wh} - p_{out})} \\ w_{lg} &= Z_{lg} C_{iv} \sqrt{\rho_a (p_a - p_{wi})} \end{aligned} \tag{7}$$

in which Z_{lg} and Z_t are the opening of the gas lift injection valves and the production choke valve, and C_{pc} and C_{iv} are the valve coefficients. p_{wh}, p_{out}, p_a and p_{wi} are the pressures at the wellhead, well outlet, annulus and injection point. ρ_w and ρ_a are the fluid densities in the well tubes and the annulus. Applying the ideal gas law, we can express the pressure in the annulus:

$$\rho_a = \frac{M p_a}{T_a R} \tag{8}$$

in which M is the gas-lift molar mass, T_a the temperature at the annulus and R the universal gas constant. The average density in the well tube is given by:

$$\rho_w = \frac{m_{gt} + m_{ot} - \rho_o L_r A_r}{L_w A_w} \tag{9}$$

where L_r,L_w and A_r,A_w are the lengths and cross-sectional area of the tubing above and below the gas injection point. The gas and oil flow from the reservoir is given by:

$$\begin{aligned} w_{ro} &= PI \cdot (p_r - p_{bh}) \\ w_{rg} &= GOR \cdot w_{ro} \end{aligned} \tag{10}$$

where PI is the productivity index, GOR is the gas-oil-ratio and p_r the reservoir pressure.

3.2 Choke valve erosion model

Erosion in choke valves by sand particles can be described with a good level of accuracy by Computational Fluid Dynamic (CFD) simulations given the valve features (DNV, 2015). However, since the optimal control problem needs to be solved online in a reasonable amount of time, a simple model is usually chosen (Seborg et al., 2010). Here, we used the semi-empirical erosion model developed by DNV (2015):

$$\dot{\varepsilon} = \frac{K \cdot F(\alpha) \cdot U_p^n}{\rho_t \cdot A_t} \cdot G \cdot C_1 \cdot G_f \cdot \dot{m}_p \cdot C_{unit} \tag{11}$$

in which ε is the erosion rate in mm, K is the material erosion constant, n is the velocity exponent, ρ_t is the valve material density; C_1 and G_F are geometry factors; C_{unit} is a unit conversion factor. U_p is the impact velocity and $\dot{m}_p$ is the sand rate that is considered to be known.

4. SIMULATION SETUP

The results are presented in two cases with different time horizons, this will provide insights into how the different layers contribute to the HAC strategy. Case 1 shows the simulations on a long horizon of 100 days, and case 2 the simulation in a short period of 4 hours. The parameters for both cases are presented in Table 1. The remaining parameter values were the same as in Matias et al. (2020). Simulations were performed in MATLAB, and the HRTO and PI MPC optimization problems were solved using CasADi software. Orthogonal collocation was used to discretize the differential-algebraic system of equations system, and the IPOPT solver was used to solve the resulting Nonlinear Programming problems.

A gas-lift oil well network with three wells was simulated, and the profit component of the objective function used in the optimal control problems was:

$$P_k = \sum_{k=0}^{n_p-1} \sum_{i=1}^{3} w_{t,i,k} \tag{12}$$

where n_p can be either n_{ph} in the HRTO problem or n_{pe} in the PI EMPC problem. The manipulated variables of the HRTO and PI EMPC were the gas-lift flow rates in the three wells, while for the PI controller, it was the opening of the gas-lift valves. Possible disturbances of the system are the GOR, PI and p_{wi}. The PI controllers were not very tightly tuned, and the effect of these tuning parameters is out of the scope of this work.

Table 1. Simulation Parameters

Parameter	Value	Parameter	Value
GOR	[10,12,11]	K_{cl}	- 1.0
PI	[5,5,5]	τ_{cl}	70
Δu_{max}	0.4	K	-0.1
n_{ph}	75 min	τ	100
n_{pe}	100 days	Δt	15 s
n_{ch}	70 days	α	1.0
n_{ce}	45 min	β	1000
u_{max}^{total}	4.5	Q_u	0.01
p_{wi}	[120, 120, 120] bar	d_{max}	1.5 mm

5. RESULTS

5.1 Case 1: Long time-horizon simulation

In the first scenario, a condition where the three choke valves in the three wells have different degradation conditions is emulated. Furthermore, a high erosion sand rate with exponential growth was chosen 100 days ahead of the subsequent planned maintenance intervention. These conditions make it possible to visualize how the HRTO could handle the erosion of the choke valves approaching the maximum erosion constraint (1.5 mm). First, Figure 3 shows the simulation without the HRTO layer. Then, only the profit (12) of the system is taken into account. As can be seen, the system operates on the economic optimal operation point until the end of the horizon, which causes the choke valve of well 1 to break down. This situation will not just cause economic losses because the oil production in well one stops, but it can also be unsafe depending

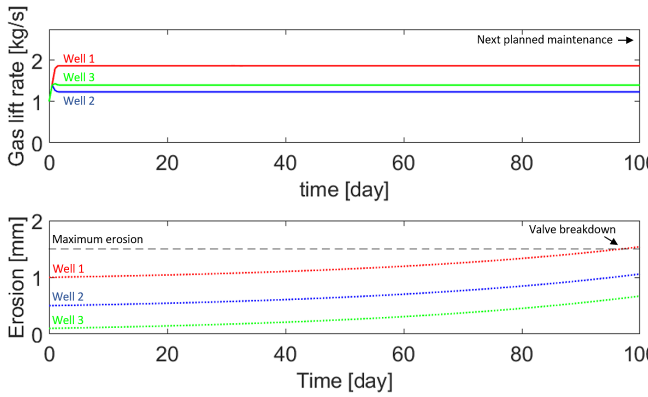

Fig. 3. Results of a simulation in a long time horizon of 100 days without the HAC strategy. At the top of the figure, the gas-lift setpoint set by the PI EMPC is shown. At the bottom, the erosion level of each choke valve is presented.

on the condition of the equipment. Therefore, an HAC is needed to ensure the valve can operate up to the next scheduled maintenance and then be replaced, avoiding unexpected maintenance interventions.

Figure 4 shows the HAC operation simulation. At the beginning of the simulation, with a lower level of choke valve degradation, the HRTO sends a high flow-rate constraint to solve the PI EMPC optimization problem. These flows are higher than the maximum physical constraint on the valves, then, in practice, no constraint is imposed on the lower layer (dotted line in the top of the figure). The PI EMPC maximizes the profit by reaching the maximum total flow constraint and spreading the gas flows among the wells based on the GOR ratio of each one.

In the final part of the simulation, the erosion level of the choke valve on well 1 began to approach the maximum erosion limit of 1.5 mm. Then, the HRTO started to slowly decrease the maximum gas-lift flow rate on that well until that constraint reached the current setpoint. Then, the PI EMPC started to decrease the production and increases the production on the other two wells to keep the maximum total rate at the maximum. This change impacts the total oil production rate because well 1 has the higher GOR. After some time, the HRTO also decreases the constraint for well two and eventually also well 3. In the end, close to the maintenance intervention, production quickly decreases.

The choke valve of well 1 was very close to the constraint at the end of the horizon, given that it is plausible to have some uncertainty in the models and degradation levels estimation. To avoid that situation, the maximum erosion can be reduced (back off constraint), or a robust method can be applied like multi-stage EMPC (Verheyleweghen and Jäschke, 2018) or worst-case scenario EMPC (Verheyleweghen, 2020). Since these robust techniques are usually computationally expensive, it is an advantage of our approach that these optimization problems are only solved in the upper layer.

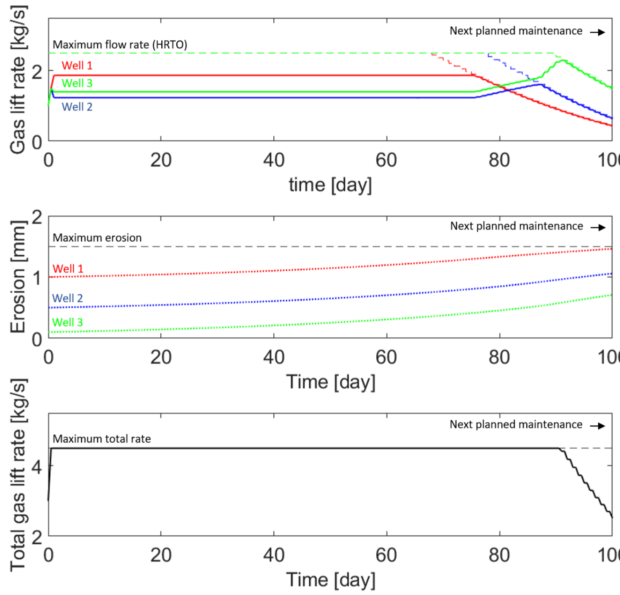

Fig. 4. Results of a simulation in a long time horizon of 100 days with the HAC. At the top of the figure, the gas-lift setpoint set by the PI EMPC is shown, together with the constraint in each well imposed by the HRTO. In the middle, the erosion level of each choke valve is presented. At the bottom of the figure, the total gas-lift rate is shown.

5.2 *Case 2: Short time-horizon simulation*

Figure 5 shows the fast time-scale simulation in hours. The gas lift rate, setpoints, and the opening valve of one of the three wells (well one) are also presented as the total gas lift rate. PI EMPC is compared with the standard EMPC without the PI controller model in order to illustrate the advantages of these layers' integration. The performance of both controllers is similar before the disturbance starts (1.4h). They increase the gas-lift setpoint until each reaches the maximum total rate constraint, corresponding to the maximum possible oil production rate. The PI EMPC seems less aggressive in changing the setpoint in this phase, and the EMPC reached maximum productivity earlier.

A disturbance starts after both systems have stabilized at the maximum productivity rate. The gas-lift pressure decreases from 120 bar to 105 bar, then in order to try to maintain the flow rate setpoint, the PI controller saturates the valve opening, but this setpoint cannot be reached anymore. Because the EMPC hasn't information about the saturated valve, the controller keeps an infeasible setpoint, and then the total gas lift is lower than the maximum possible, leading to sub-optimal economic performance. On the other hand, the PI MPC has the information about the saturated valve but can also plan the next control action to counteract that saturation. Then, the controller decreases the gas-lift rate on that well, and increases on the other two, keeping the maximum total rate.

After the disturbance is finished, an increase in the gas-lift rate occurs. The EMPC violates not only the maximum total rate constraint but also the maximum individual flow rate sent by the upper layer (HRTO). Eventually, the

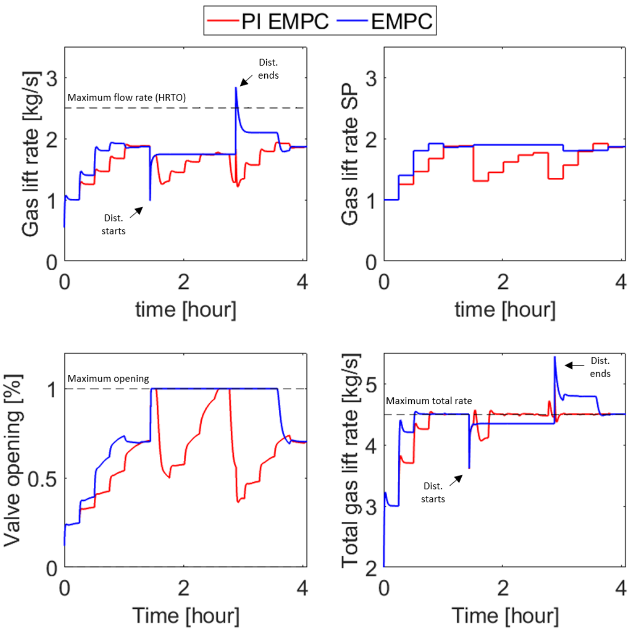

Fig. 5. PI EMPC and EMPC performance in the presence of disturbances. At the top, the measured gas-lift rate and the gas-lift rate setpoints are shown. At the bottom, the valve opening and the total gas lift rate is presented. The results correspond to well 1, the other wells' variables were omitted. A disturbance in the gas-lift pressure started at 1.4h and ended after two hours.

EMPC was able to decrease the setpoint and stabilize the system. However, the PI EMPC is much quicker to perform that task.

6. DISCUSSION

The present work had as its main goal to get insights into the multi-layer strategy for the HAC. One advantage of this time-scale separation is the possibility of solving the most challenging problem on the upper layer since the time to solve the HRTO problem was, on average, ten times the time to solve the PI EMPC problem, which can be worse with long horizons and if robust methods are applied. Adding the PI controller model on the EMPC also seems promising since violating the flow rate constraint can increase degradation in the long run.

Full-state information and perfect degradation level information were assumed in the simulations. In practice measures for dealing with this uncertainty have to be taken (Verheyleweghen, 2020). Furthermore, the threshold for the maximum degradation can have a considerable impact on the HRTO layer, the proper definition of that variable is crucial. Note also that the same process model was considered in both layers. However, it could be the case that a better steady-state model is available for the HRTO layer. In that case, using the lower layer as a setpoint tracking MPC should be considered instead.

7. CONCLUSION

The results suggest that the time decomposition in the HAC is a suitable approach to deal with the significant differences in time scales. Future works should focus on how the maintenance planning layer can be integrated into that strategy. Also, the horizontal (space) decomposition for HAC can be investigated.

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