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Modeling and Nonlinear Model Predictive Control of a Subsea Pump Station ⋆

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Abstract: In this paper we present a model of a pump station consisting of two pumps in parallel with a recycle line, and a nonlinear Model Predictive Control strategy for said pump station with suction pressure as the controlled variable. The dynamics of the flow through the pump station is described using slightly modified models previously presented for electrical submersible pumps. By using the symbolic framework CasADi in Matlab, we solve the nonlinear optimal control problem by first discretizing it using the single shooting method and then solving the finite-horizon nonlinear program. Simulations in Simulink shows that the proposed solution is able to track the suction pressure reference under various conditions and disturbances, while respecting constraints.

Keywords: Modeling and system identification, Process Control, Pumps, Subsea Boosting

1. INTRODUCTION

After years of production from an oil-field, the pressure in a reservoir will decline. This leads to lower production unless the pressure is either maintained by pumping water or gas into the reservoir or the pressure downstream the well is reduced (Bai and Bai, 2012). Boosting reduces the back pressure seen by the well, which causes a higher flow rate of produced fluids from the well and hence allows for a longer tail end production or, if boosting is installed from the beginning of production, a higher production plateau.

Subsea boosting was introduced in the 90's and aims at accelerating and prolonging the production plateaus of economically marginal subsea fields. Subsea boosting enables tie-backs from satellite fields to existing production facilities (Solvik et al., 2013). As an example, Statoil estimated that the installation of a subsea processing unit consisting of water separation and pressure boosting would increase the recovery factor from 49 to 55% and extract an additional 35 million barrels of oil from the Tordis field (Gjerdseth et al., 2007). The typical impact of boosting on a brown field (old field) is depicted in Fig. 1.

A subsea production manifold experiences a back pressure equal to the hydrostatic pressure of the riser, which can be hundreds of meters tall, e.g., the Tordis Field (Gjerdseth et al., 2007). By inserting a boosting station, this back pressure can be reduced, which in turn leads to an increased or prolonged production. The boosting station also helps bringing the produced hydrocarbons topside by increasing the pressure downstream the station. The

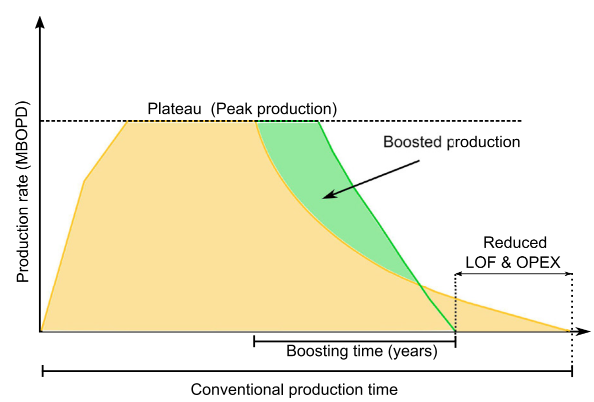

Fig. 1. Boosting in a brown field (old field) typically yields additional production and leads to a reduced life of field and hence, reduced operational expenditures (OPEX).

boosting station consists of one or more pumps and associated support systems.

Model predictive control (MPC) is commonly used in the process industry because it combines control, either tracking or regulation, with constraint handling (Camacho and Alba, 2013). While linear MPC has been a preferred method of control in the industry for several decades, nonlinear MPC (NMPC) is still fairly uncommon. While linear MPC only considers a linear prediction model, either based on step-responses or linearization, the NMPC has the ability to take system nonlinearities into account. However, the complexity of the problem, with regards to computational time and tuning, increases with the use of NMPC (Allgower, 2005).

Recent papers, (Pavlov et al. (2014); Krishnamoorthy et al. (2016); Binder et al. (2014)), presents linear MPC

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strategies for electric submersible pumps (ESPs). These pumps are submerged into the oil-well and uses the same principle of suction pressure reduction to increase production as the multiphase pumps. In Pavlov et al. (2014), a simple model of an ESP-lifted oil-well was presented and a linear MPC developed based on step responses. The results from simulations and large scale tests showed that the linear MPC performed well.

The robustness of the MPC was put to test in Krishnamoorthy et al. (2016), where a high fidelity simulator was developed in Modelica. The process was tested with different water cuts and the controller showed sufficient robustness. In Binder et al. (2014) the MPC algorithm was implemented on a PLC, and hardware-in-the-loop simulations showed that the control performance of the PLC implementation matched that of the original controller which was developed using Statoil's in-house software tool for MPC, SEPTIC (Strand and Sagli, 2003). In fact, SEPTIC was used in all the papers Pavlov et al. (2014); Krishnamoorthy et al. (2016); Binder et al. (2014).

Nonlinear optimal control of ESPs was investigated in Sharma and Glemmestad (2013) where a steady state optimizer calculated the optimal fluid flow rate and pump speeds for several pumps in parallel. The flow rates and speeds were used as setpoints to two PI controllers which set the pump speed and production choke opening. Since the optimizer was based on steady-state, it had to be rerun every time a process disturbance occurred.

Optimal control and scheduling of multi-pump systems was studied in Yang and Børsting (2010b) and Yang and Børsting (2010a). Here, a mixed integer nonlinear program was solved to determine the number of pumps to put into operation. Feedback control was used to counter the uncertainties in the optimizer. In Yang and Børsting (2010a) an identification algorithm was derived to estimate unknown system parameters. The resulting optimizer was tested on a test rig and showed a significant improvement of the pump system's efficiency.

Model predictive control of a pump system with parallel pumps was investigated in Becquin et al. (2015). Here, the process simulator K-spice and the multiphase flow simulator LedaFlow were used to accurately model the pump station and flow lines. These high fidelity simulators were linked with Simulink, where the MPC algorithm was implemented. Simulations of the start-up procedure was presented and the simulations showed that the proposed control solution worked very well.

In this paper we present a simple model of a subsea pump station with a recycle line. The model is a modified version of the model for ESP-lifted wells used in Pavlov et al. (2014); Krishnamoorthy et al. (2016); Binder et al. (2014). We then propose a control solution using an NMPC that controls the speed of the multiphase pumps with the goal of bringing the suction pressure to the desired setpoint while considering the constraints on the system. The NMPC control problem is solved in Matlab using the symbolic framework CasADi v.3.1.0-rc1. CasADi is a free, open-source software tool for nonlinear optimization (Andersson et al., 2012).

The paper is organized as follows: Section II describes the process and the model used in simulations. The NMPC controller is presented in Section III along with the control objectives. Section IV contains the results of the simulations and Section V concludes the paper.

2. MODELING

The system consists of two multiphase pumps in parallel and a recycle line. The model of the pressure and flow is based on a model which has previously been used to describe ESPs in Pavlov et al. (2014), Binder et al. (2014) and Krishnamoorthy et al. (2016). We use this model, which describes flow through vertical pumps, to describe the flow through horizontal pumps by modifying it slightly. An overview of the system is shown in Fig. 2.

Several wells are producing to a manifold with pressure P_m. In the design of the controller we consider this to be nominally constant, but we introduce variations to it in the simulations.

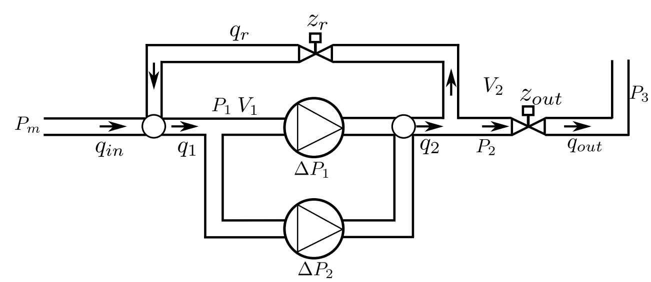

Fig. 2. Subsea pump station with two pumps in parallel and recycle line.

The recycle line is included to ensure that the pumps receive the minimum allowed flow at all times. The flow that enters the pump inlets is the sum of the inlet flow and the recycle flow. We assume that the flow is incompressible, hence the flow that enters the pumps, q_1, is the same flow that exits the pumps, q_2.

2.1 Pumps

A common way to describe the relationship between flow, head and speed of a pump is to use affinity laws as described in Takács (2009). The affinity laws state that the pressure difference over a pump changes proportionally to the square of the speed and that the power required to drive the pump changes proportionally to the cube of the speed. The expressions for pump j are

$$\Delta P_j(\omega_j) = P_{j,0}(q_{j,0}) \left(\frac{\omega_j}{\omega_{j,0}} \right)^2 \tag{1}$$

$$\Phi_j(\omega_j) = \Phi_{j,0}(q_{j,0}) \left(\frac{\omega_j}{\omega_{j,0}} \right)^3 \tag{2}$$

where ΔP_j [Pa] is the pressure increase provided by the pump, Φ_j [W] is the power consumed by the pump, ω_j [rpm] is the speed of the pump, $P_{j,0}(q_{j,0})$ [Pa] is the pressure increase at a given nominal flow $q_{j,0}$ [m^3/s] and a given nominal speed $\omega_{j,0}$ [rpm]. $\Phi_{j,0}$ [W] is the power consumption at nominal flow $q_{j,0}$ and nominal speed $\omega_{j,0}$. The affinity laws only hold for incompressible fluids, so in this paper we assume that the fluid is incompressible in the pumps and instead reduce the nominal pressure increase of the pump to account for the gas; a higher compressibility reduces the volumetric efficiency of pumps as described in Nesbitt (2006).

2.2 Pressure and flow dynamics

The pressure upstream and downstream the pumps are modelled using mass balances following Egeland and Gravdahl (2002). The mass balance for a control volume V is given by

$$\frac{\mathrm{d}}{\mathrm{dt}}(\rho V) = w_i - w_o \tag{3}$$

where $w_i = \rho q_i$ [kg/s] is the mass flow and q_i [m^3/s] is the volumetric flow into the volume, while $w_o = \rho q_o$ [kg/s] is the mass flow and q_o [m^3/s] is the volumetric flow out of the volume. Inserting this into (3) and using $\dot{V} = 0$ (incompressible fluid) gives

$$\dot{\rho} V = \rho (q_i - q_o) \ . \tag{4}$$

Pressure and density are related by their differentials by

$$\frac{\mathrm{d}\rho}{\rho} = \frac{\mathrm{d}P}{\beta} \tag{5}$$

where β [Pa] is the bulk modulus of the fluid. For the two volumes V_1 and V_2 and pressures P_1 and P_2 (Fig. 2), we then get

$$\dot{P}_1 = \frac{\beta}{V_1}(q_{in} + q_r - q_2) \tag{6}$$

$$\dot{P}_2 = \frac{\beta}{V_2}(q_2 - q_r - q_{out}) \ . \tag{7}$$

The different flows are the flow from the manifold q_{in}, the recycle flow q_r, the flow through the pumps q_2 and the outlet flow q_{out}. Note that since we assume that the flow through the pumps is incompressible, $q_{in} = q_{out}$ and $q_2 = q_{in} + q_r = q_1$. The flows q_{in}, q_r and q_{out} are described by orifice equations

$$q_{in} = C_{d,in} A_{in} \sqrt{\frac{(P_m - P_1)}{\rho}} \tag{8}$$

$$q_r = C_{d,r} A_r z_r \sqrt{\frac{(P_2 - P_1)}{\rho}} \tag{9}$$

$$q_{out} = C_{d,out} A_{out} z_{out} \sqrt{\frac{(P_2 - P_3)}{\rho}} \tag{10}$$

where P_m is the pressure at the manifold, $C_{d,in}, C_{d,r}, C_{d,out} \in (0, 1]$ are the discharge coefficients, A_{in}, A_r and A_{out} are the cross-sectional areas of the pipes at the inlet, recycle line and outlet, respectively. The valve openings of the recycle line and outlet valve are represented by $z_r \in [0, 1]$ (between 0 and 1) and $z_{out} \in \{0, 1\}$ (either 0 or 1).

The dynamics of the flow after the pumps, q_2, is described by mass balances in the same manner as in Pavlov et al. (2014), Krishnamoorthy et al. (2016) and Binder et al. (2014)

$$\dot{q}_2 = \frac{1}{M}(P_1 - P_2 - P_3 + \Delta P_1 + \Delta P_2) \tag{11}$$

where the fluid inertia is described by $M = \frac{\rho l}{A_p}$[kg/m^4] where l is the length of the pipes between the pumps and the outlet choke valve and A_p is the cross-sectional area of the pipes. $\Delta P_j, j \in \{1, 2\}$ is the pressure increase provided by each pump. Inserting (1) into (11) gives

$$\dot{q}_2 = \frac{1}{M}\left(P_1 - P_2 - P_3 + P_{1,0}(q_{1,0})\left(\frac{\omega_1}{\omega_{1,0}}\right)^2 + P_{2,0}(q_{2,0})\left(\frac{\omega_2}{\omega_{2,0}}\right)^2\right) \tag{12}$$

where ω_1 and ω_2 are the speeds of Pump 1 and Pump 2, respectively. The system is then given by (6), (7) and (12).

3. CONTROL

3.1 Control objectives

We wish to use the pumps to maintain a desired suction pressure $P_{1,d}$. The pumps are constrained by their maximum speed and maximum allowed change in speed, as well as maximum available power. In addition, due to safety concerns and the requirements of the topside production equipment, the flow should be kept as steady as possible and there is a maximum allowable flow rate.

In this paper we only investigate normal operation of the pump station, i.e., we do not consider start-up or shutdown sequences. Pressure and flow are assumed continuously measured, no observer is used and no process noise is added. Measurement noise is used in some simulations.

3.2 Limits

The pump model is in the following based on reasonable/typical performance limits. The pumps are assumed to be limited by a maximum power consumption, $\Phi_{\max} = 2235$ kW. The rotation speed of each pump, under normal operation, is limited to between $\omega_{\min} = 500$ rpm and $\omega_{\max} = 3800$ rpm. The maximum allowed change in pump speed is $\Delta w_{\max} = 60$ rpm/s. The topside receiving facility limits the maximum allowed fluid flow to $q_{\text{out,max}} = 1900$ m^3/h.

3.3 Control design and implementation

The process, described by (6), (7) and (12), contains nonlinearities, and since the controlled variables and manipulated variables are subject to constraints, a nonlinear model predictive controller (NMPC) is proposed as control solution.

We define the tracking error as $\tilde{P}_1 = P_1 - P_{1,d}$ where $P_{1,d}$ is the desired suction pressure. The continuous-time optimal control problem (OCP) is formulated as

$$\min_{\tilde{P}_1, q_2(t)} \int_0^T \left(\frac{\gamma_1}{\tilde{P}_{1,\max}^2}\tilde{P}_1^2 + \frac{\gamma_2}{\dot{q}_{2,\max}^2}\dot{q}_2^2\right) \mathrm{d}t \tag{13}$$

over the time horizon T. The first term ensures reference tracking while the second term attempts to maintain a constant flow. The weights $\gamma_1, \gamma_2 \geq 0$ are the weights on the reference tracking and change in flow respectively. The division by $\tilde{P}_{1,\max}^2$ and $\dot{q}_{2,\max}^2$ ensures that the weights are normalized. Note that the inputs w_1, w_2 do not directly enter the cost function; cost is only associated with changes in total pump flow q_2.

The OCP is subject to the inequality constraints

$$|\Delta\omega| \leq \Delta\omega_{\max} \tag{14a}$$
$$-P_1(t) \leq -P_{1,\min} \tag{14b}$$
$$0 \leq \Phi \leq \Phi_{\max} \tag{14c}$$
$$q_{2,\text{low}} \leq q_2 \leq q_{2,\max} \tag{14d}$$

and the equality constraints describing the system dynamics

$$\dot{P}_1 = f_1(q_{in}(t), q_r(t), q_2(t)) \tag{15}$$
$$\dot{P}_2 = f_2(q_2(t), q_r(t), q_{out}(t)) \tag{16}$$
$$\dot{q}_2 = f_3(P_1(t), P_2(t), P_3(t), \omega(t)) \tag{17}$$

with given initial conditions $P_1(0), P_2(0), q_2(0)$ and functions f_1, f_2, f_3 defined by (6), (7) and (12), respectively.

The NMPC algorithm seeks to repeatedly solve a finite-horizon optimal control problem using the latest measurements as initial states $P_1(0), P_2(0), q_2(0)$. The solution to the optimal control problem is a sequence of piecewise constant inputs that minimizes the cost function while satisfying the constraints. Only the first optimal input is used, and then new optimal inputs are calculated when the algorithm runs again at the next time step.

In order to solve the nonlinear OCP we first transcribe the infinite dimension OCP described by (13)–(17) into a discrete-time finite dimension OCP. In this paper we use the *direct single-shooting* method, as described in Johansen (2011), to eliminate the continuous-time dynamics. We use a 4th order Runge-Kutta method with a step length of 0.01 second to solve the discrete dynamics of the prediction model in the MPC algorithm. The control $\omega(t)$ is realized by piecewise constant controls ω_k on a fixed, evenly spaced grid $0 = t_0 < t_1 < \ldots < t_N = T$ of N intervals $k = 0, \ldots, N-1$, i.e.,

$$\omega(t) = \omega_k \ \text{ if } t \in [t_k, t_{k+1}) \, . \tag{18}$$

3.4 Recycle loop control

The recycle loop ensures that the pumps receive the minimum required inlet flow. The recycle loop valve is controlled with a PI controller. The NMPC receives a measurement of the recycle loop flow and uses this in the prediction model, but otherwise the two control loops are completely independent.

It is useful to always have a certain recycle flow to avoid temperature issues in the recycle loop, hence the recycle control valve is typically never less than 20% open. If the inlet flow is higher than the minimum flow we do not want to close the valve and bring the flow down, hence the proportional part of the PI controller is only activated if the actual inlet flow is lower than the minimum limit. Since the minimum valve opening is 20% the contribution from the integrator is limited between 20% and 100% to avoid windup issues. The error variable for the PI controller is defined as $e \triangleq q_{1,\min} - q_1$. The recycle loop control solution is depicted in Fig. 3.

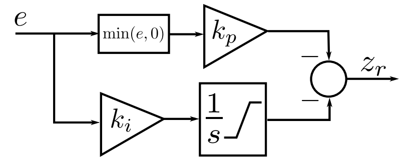

Fig. 3. PI controller solution. The proportional part is only activated if the flow is less than the minimum. The integral contribution is limited to between 0.2 and 1 to avoid windup issues.

4. RESULTS

The process model consisting of (6), (7) and (11) was implemented in Simulink. We used Matlab and the symbolic framework CasADi to solve the OCP by first discretizing using single shooting and then solving the resulting nonlinear program with the IPOPT solver.

We tested 3 different scenarios in this paper. In the first scenario, we consider identical pumps and introduce a disturbance to the upstream conditions which causes the inlet flow to decrease. This will cause the recycle loop control system to open the valve and increase the recycle loop flow to ensure that the minimum flow requirements are met.

The second scenario is the same as the first scenario, but we introduce additive zero-mean Gaussian white noise to the measurements prior to the NMPC. The noise has a variance of 3% of the normal value of the measurement and all noise generators use different seeds (i.e., are uncorrelated).

In the third scenario we consider pumps with different ω_0, P_0 and Φ_0. The nominal speed of Pump 2 is changed to $\omega_{0,2} = 2600$ rpm, the nominal pressure increase to $P_{2,0} = 25$ bar and the nominal power consumption to $\Phi_{2,0} = 1000$ kW. We use the same measurement noise as in Scenario 2.

In all scenarios we introduce a positive step from 15.3 to 25.3 bar in the downstream pressure P_3 at $t = 300$ s and a step back to 15.3 bar at $t = 600$ s. The process is initialized with $q_2(0) = 900\,\text{m}^3/\text{h}$, $P_1(0) = 30\,\text{bar}$ and $P_2(0) = 35\,\text{bar}$. We used the ode45 solver in all simulations. The NMPC algorithm runs every second and a zero order hold block keeps the measurements constant between samples. The values used in the model is presented in Table 1 and the parameters used in simulation of Scenario 1 and 2 in Table 2 and Scenario 3 in Table 3.

Table 1. Model parameters

Parameter	Value	Description
β	10^9 [Pa]	Bulk modulus
ρ	600 [kg/m^3]	Density of fluid
V_1	1.6215 [m^3]	Volume upstream pumps
V_2	0.8107 [m^3]	Volume downstream pumps
$C_{d,in}$	0.55[-]	Discharge coeff., inlet
$C_{d,r}$	1[-]	Discharge coeff., recycle loop
$C_{d,out}$	0.55 [-]	Discharge coeff., outlet
A_x	0.0081 [m^2]	Pipe cross section areas
l	50 [m]	Pipe length, pump to outlet
z_{out}	1[-]	Outlet valve opening
$\tilde{P}_{1,\max}$	4×10^6 [Pa]	Normalizing factor
$\dot{q}_{2,\max}$	0.1 [m^3/s^2]	Normalizing factor

Table 2. Parameters used in Scenario 1 and 2

Parameter	Value	Unit
P_m	5×10^6	Pa
P_3	1.53×10^6	Pa
γ_1, γ_2	100, 10	-
T	3	s
N	3	-
$\omega_{1,0}$, $\omega_{2,0}$	3300	rpm
$P_{1,0}$, $P_{2,0}$	2.3×10^6	Pa
$\Phi_{1,0}$, $\Phi_{2,0}$	1500×10^3	W
k_p	20	s/m^3
k_i	10	s^2/m^3

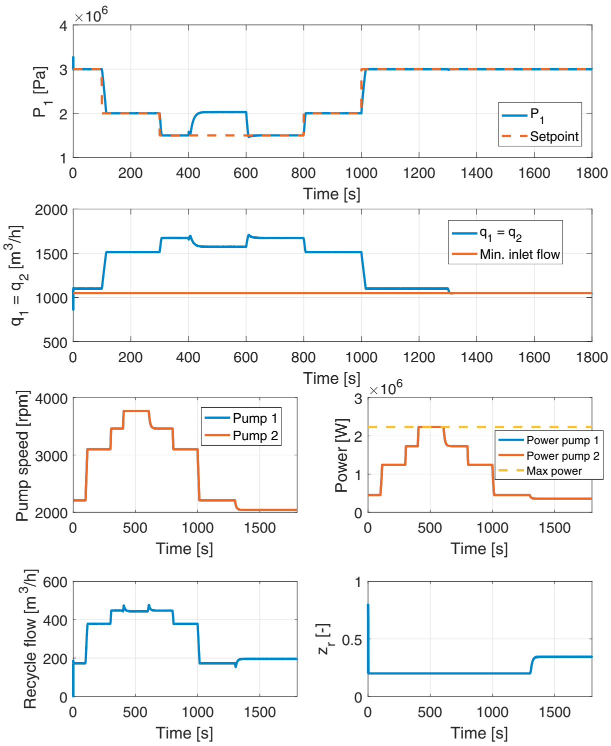

Fig. 4. Scenario 1 simulation results.

4.1 Scenario 1: Identical pumps, upstream disturbance, no measurement noise

As can be seen from Fig. 4, the NMPC is able to track the desired setpoint while respecting the constraints on change in pump speed and maximum power. When the step in the downstream pressure occurs at $t = 300$ s, the pumps are initially able to maintain the setpoint, but then the power constraint is met which leads to the deviation between setpoint and measurement between $t \sim 400$ s and $t \sim 700$ s.

At $t = 1300$ s, the upstream disturbance occurs and, as shown in Fig. 4, it takes approximately 50 seconds for the flow to reach the minimum limit and cause the recycle control loop to engage. The valve opens, the recycle flow increases and hence, the inlet flow is brought back to the minimum value for the remainder of the simulation.

4.2 Scenario 2: Identical pumps, upstream disturbance, measurement noise

In this scenario we introduce measurement noise to all measurements used in the NMPC algorithm, i.e,

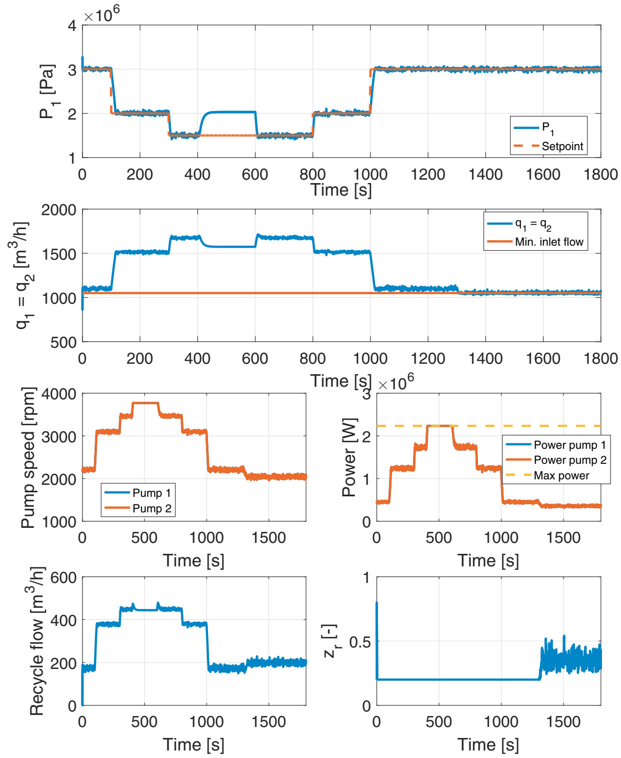

Fig. 5. Scenario 2 simulation results.

P_1, P_2, P_3, P_m, q_2 and q_r. The results are shown in Fig. 5, where we see that the NMPC is still able to produce inputs for the pumps that enables setpoint tracking and constraint handling. The minimum inflow boundary is breached at certain points due to the magnitude of the measurement noise and the sampling time of the NMPC. This could probably have been improved by filtering the measurements before using them in the NMPC, or by increasing the sampling time of the NMPC algorithm. Another solution is to add a back-off to prevent the minimum flow from reaching the actual minimum flow. The downside of this is that more fluid than strictly necessary is recycled, which leads to reduced production.

4.3 Scenario 3: Non-identical pumps, upstream disturbance, measurement noise

We now change the nominal speed of Pump 2 to $\omega_{2,0} = 2600$ rpm, the nominal pressure increase to $\Delta P_{2,0} = 25$ bar and the nominal power consumption to $\Phi_{2,0} = 1000$ kW. This implies that Pump 2 can produce a higher pressure increase at a lower speed and that its power consumption is slightly higher than that of Pump 1. As shown in Fig. 6, there is a difference in the pump speeds and power consumptions of Pump 1 and Pump 2. Due to the increased pressure increment provided by Pump 2, we are now able to better track the setpoint when the downstream disturbance occurs at $t = 400$ s.

5. CONCLUSION

In this paper we have presented a model of, and a nonlinear Model Predictive Control solution for, a subsea pump station with two pumps in parallel with a recycle line. Simulations show that the solution is robust to measurement noise and is able to achieve the objective, but the

Table 3. Parameters used in Scenario 3

Parameter	Value	Unit
P_m	5×10^6	Pa
P_3	1.53×10^6	Pa
γ_1, γ_2	100, 10	-
T	3	s
N	3	-
$\omega_{1,0}$, $\omega_{2,0}$	3300, 2600	rpm
$P_{1,0}$, $P_{2,0}$	2.3×10^6, 2.5×10^6	Pa
$\Phi_{1,0}$, $\Phi_{2,0}$	1500×10^3, 1000×10^3	W
k_p	20	s/m^3
k_i	10	s^2/m^3

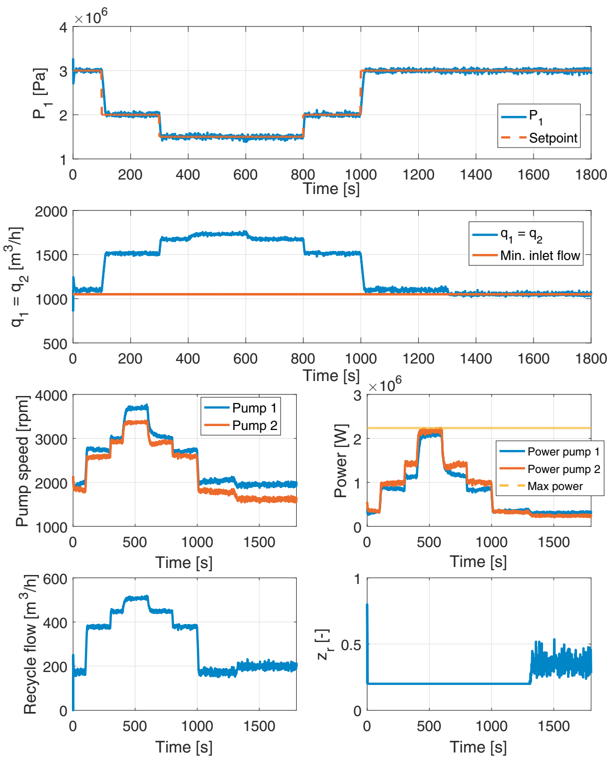

Fig. 6. Scenario 3 simulation results.

minimum flow constraint is breached at certain points. To avoid this one could introduce a filter or back off further from the true constraint.

The NMPC solution also works when the two pumps have different efficiency. This opens for more varied optimal control schemes. One could for instance allocate more production to the most effective pump. Implementing this in the controller remains future work.

The recycle line control valve can be added to the MPC algorithm. Investigating this scheme remains future work. Currently, the controller uses what is effectively a single-phase pump model; a true multiphase pump model is desirable as subsea boosting is frequently multi-phase. Both developing the model and the controller for this model remains future work.

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