Standard MPC and Inputs-Target MPC implementation comparison in ESP systems.

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Abstract: Electric submersible pump (ESP) systems are essential in the oil industry. These systems allow operation with high flow rates and efficiency, even in mature and deep wells. This paper compares the practical implementation of Model Predictive Controllers (MPC) in an ESP system in the Artificial Lift Laboratory at UFBA. The first controller is the traditional MPC, and the second is a target MPC with targets at the input. The zone controller is a more advantageous option for the scenarios tested since tuning is more straightforward, has an easy operating point for the operator to understand, and operates naturally in the maximum production region.

Keywords: Process control applications, Model predictive and optimization-based control, Industrial applications of process control

1. INTRODUCTION

Artificial lift systems have become increasingly crucial in oil and gas production due to several factors, including the maturity of currently explored oil wells, increased competition, geopolitical factors, more efficient production and the need for cleaner production with lower greenhouse gas emissions. In this context, electric submersible pump (ESP) based lift systems play a fundamental role, as they can pump high flow rates and tolerate multiphase operation.

The control of ESP systems has historically been performed manually with some documented implementations Binder et al. (2014); Pavlov et al. (2014); Binder et al. (2015); Krishnamoorthy et al. (2016); Delou et al. (2019). The challenge in controlling ESP systems is the safety and process constraints that need to be considered, including the upstream and downstream regions. Additionally, as the system has two manipulated variables and several controlled variables Binder et al. (2015); Pavlov et al. (2014); Costa et al. (2021), it implies a series of constraints that must be evaluated at all times. In this ESP system control scenario, the natural path implements Model Predictive Controllers (MPC) controllers to stabilise the process and keep it within the constraints.

Pavlov et al. (2014) presents the ESP model coupled with MPC. The authors showed the relationship between the operating envelope of the ESP system and connected it to a controller. This allows constraints to be incorporated directly into the controller and to monitor the balance of internal forces in the pump.

Binder et al. (2014) presented the implementation of an MPC controller embedded in a programmable logic controller (PLC) for ESP-operated systems. Binder and collaborators directly discussed the aspects of the real-time implementation in PLC. This embedded approach has some limitations, mainly in updating the tuning and the controller, since local access to the PLC is required.

In turn, Binder et al. (2015) deals with an essential part of implementing the MPC control: the moving horizon state estimators. It proposes using these to estimate the average flow rate and viscosity of the oil pumped in the well. On another front, Krishnamoorthy et al. (2016) presents an advanced regulatory control arrangement based on PID and Split-Range. This work presents relevant discussions on production with ESP, including the simplicity of the controllers. However, for implementation in natural systems, this controller must operate with a larger back-off to prevent the system from tripping due to violation of the envelope variables.

In more recent works, Jordanou et al. (2022) presented the basis for the construction of MPC controllers using Echo State networks (ESNs) and de Abreu et al. (2024) presented advances in the treatment of the NMPC controller to create the basis for the implementation of Nonlinear Model Predictive Control (NMPC) by range.

The challenge in implementing MPC controllers is obtaining models. On the other hand, the models are already well-established and validated in the literature for ESP systems Binder et al. (2014); Pavlov et al. (2014); Binder et al. (2015); Krishnamoorthy et al. (2016); Delou et al. (2019); Sharma and Glemmestad (2013); Costa et al. (2021), so the implementation and construction of MPCs can be explored and implemented in practice.

This paper presents the results of implementing and comparing two MPC controller approaches for ESP systems: MPC with setpoint tracking and MPC with input targets and zones. This work will use this knowledge in ESP modelling and control to advance the field´s state of the art by exploring more complex and experimentally implemented control strategies. These are presented with the objectives of stabilising the system and respecting the constraints. Not much literature was found about evaluating zone-MPC with target controllers, especially about control and process performance. This paper explores these techniques further, presents real-time implementation results, and evaluates the operation in terms of throughput maximisation. Each approach has specific control characteristics, and both were implemented in real-time in a solution based on the Petrobras MPA system (Campos et al., 2001). The paper is structured as follows. Section 2 presents the main elements of the methodology, Section 3 discusses the results, and Section 4 concludes the paper.

2. METHODOLOGY

2.1 System description

The ESP system used in this article as a case study is a pilot unit located at the Federal University of Bahia in Salvador in the Artificial Lift Laboratory. The system consists of a 32 m high pipe with a 15-stage submersible centrifugal pump with an 18 Hp motor. All the installed instrumentation is commonly used in the industry and is equivalent to that used in a real oil field. The system is instrumented with a choke valve installed at the top of the unit, a Coriolis flow sensor installed after the choke valve, and temperature and pressure sensors along the well, including measurements through the bottom sensor installed in the pump assembly, as shown in Figure 1. Further details about the installation can be seen in Costa et al. (2021); Rebello et al. (2024). The system has two manipulated variables, f and Zc and three states: q_c, P_{in} and H. The other instrumented variables in the diagram of Figure 1 can be used to monitor the system during the experiment execution.

2.2 Modeling

Costa et al. (2021) presents the ESP system's validated model, consisting of three differential equations and some associated algebraic equations. To build the controller, however, the model was linearised around strategic operating points for implementation. The final model used was assembled in the augmented state vector format proposed by Maciejowski and Huzmezan (2007):

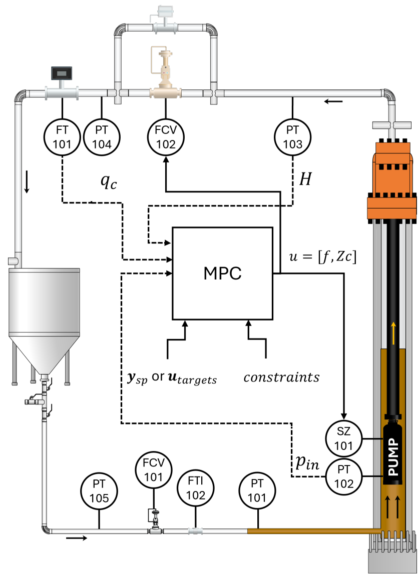

Fig. 1. LEA process diagram flow sheet.

$$\dot{x}(t) = \begin{bmatrix} A & B \\ 0 & I \end{bmatrix} x(t) + \begin{bmatrix} B \\ I \end{bmatrix} \Delta u(t), \tag{1}$$

$$y(t) = [C \;\; 0]\, x(t), \tag{2}$$

in which $x(t)$ and $\Delta u(t) = u(t) - u(t-1)$ are the state vector and the incremental actions, respectively. $y(t)$ is the output vectors, and A, B, C e D are the state-space matrices that can be obtained from the linearisation of the model from Costa et al. (2021) in the desired steady-state.

2.3 Standard MPC

The first control approach tested refers to what the literature proposes as a standard MPC cost function as presented by Maciejowski and Huzmezan (2007); Camacho and Bordons (2007):

$$J_1 = \sum_{j=1}^{Hp} \|y(k+j|k) - y_{\text{sp}}(k)\|^2_{Q_y} + \sum_{j=0}^{Hc-1} \|\Delta u(k+j|k)\|^2_R,$$

and the control optimization problem as:

$$\min_{\Delta u_k} J_1$$

Subject to:

$$\boldsymbol{u}_{\min} \leq \boldsymbol{u}(k-1) + \sum_{i=0}^{j} \boldsymbol{\Delta u}(k+i|k) \leq \boldsymbol{u}_{\max} \tag{3}$$

$$-\boldsymbol{\Delta u}_{\max} \leq \boldsymbol{\Delta u}(k+j|k) \leq \boldsymbol{\Delta u}_{\max}, j = 0, \ldots, Hc-1 \tag{4}$$

$$\boldsymbol{\Delta u}(k+j|k) = 0, \ \forall j \geq Hc \tag{5}$$

$$Hp \geq Hc, \tag{6}$$

$$\boldsymbol{y}_{\min}(k) \leq \boldsymbol{y}(k+j|k) \leq \boldsymbol{y}_{\max}(k), j = 1, \ldots, Hp, \tag{7}$$

in which Hp, Hc, Q_y and R are tuning parameters, respectively, the prediction and control horizon and the inputs and outputs weights matrices.

The boundary conditions (3) to (7) include all the constraints in this controller. Equation (3) is the actuator's physical limits, that is, the minimum and maximum values limit of the control actions. (4) is the constraint in the rate of the actuators. (5) imposes the control actions in zero after the control horizon, in other words, terminal cost constraint. (6) imply that the prediction horizon is higher than the control horizon, and (7) impose the output constraints.

The theoretical hypotheses and limitations of the presented MPC formulation are well discussed in Maciejowski and Huzmezan (2007) and later works. The main objective of this work was to implement a practical MPC to control an ESP pump system.

2.4 Input target MPC

The second control approach tested in this paper is the input target controller following the ideas presented in some works such as Ferramosca et al. (2010), González and Odloak (2009). The cost function of this controller can be defined as:

$$
\begin{aligned}
J_2 = &\sum_{j=1}^{Hp} \|y(k+j|k) - y_{\mathrm{sp}}(k)\|^2_{Q_y} \\
&+ \sum_{j=1}^{Hc} \|u(k+j|k) - u_{\mathrm{des},k}\|^2_{Q_u} \\
&+ \sum_{j=0}^{Hc-1} \|\Delta u(k+j|k)\|^2_R
\end{aligned} \tag{8}
$$

The control problem is, then:

$$
\min_{\boldsymbol{\Delta u}_k, \boldsymbol{y}_{sp}} J_2
$$

Subject to (3), (4), (5), (6) and (7).

This cost function differs from the MPC in (2.3) only by the second term in the objective function (8). This term ponders the distance between the calculated control actions and the desired input targets; the setpoints are also decision variables in this problem. However, the exact cost function is obtained by imposing $Q_u = 0$ as suggested by Maciejowski and Huzmezan (2007); Ferramosca et al. (2010)

Additionally, Ferramosca et al. (2010) argues that the domain of attraction of the range controller solution is potentially more extensive than the standard formulation presented in Section 2.3. This implies that the range controller has a reduced potential to present infeasible solutions since the controller has a greater degree of freedom to choose between the control actions and the desired output value.

2.5 Implementation aspects

The two controllers were implemented using the MPA (Automatic Procedures Podule. From the Portuguese definition: Módulo de Procedimentos Automáticos) solution. The MPA is an industrial plant management software that operates in real-time, directly communicates with sensors and actuators and replaces conventional distributed control systems (DSC) systems (Campos et al., 2001). Thus, to implement the MPCs, an application in C++ was developed to solve the MPC quadratic programming (QP) problem and compiled as an executable file. This application receives the measured values from the system outputs, updates the controller states based on a conventional Kalman filter and solves the QP using the QPOASEs library (Ferreau et al., 2014), which is also written in C++. This allows the solution process to avoid interference during real-time execution. On the other hand, the MPC controller is a passive entity in this structure, so the MPA is responsible for the control loop collecting data through OPC and delivering it to the controller. This C++ solved the QP problem in ≈ 400 milliseconds of execution.

3. RESULTS

The results below present four distinct scenarios with specific control characteristics and challenges. The first two refer to the traditional MPC controller, and the next two refer to the zone controller with targets at the inputs. The overall MPC configuration parameters found by simulations are shown in Table 1, which presents the operating points at which the models were linearised and the tunings used in the controllers.

An average filter was included in the implementation of these controllers. The system has a base sample time equal to 1 second, and the controller is implemented with a sampling time of 30 seconds. It was then assumed that the value of the measured variable is composed of the average of the 30 samples collected between the controller implementations. This considerably reduced the noise passed to the controller. However, some noise is still present, as can be seen, mainly in the Head variable in Figures 2 to 4.

Scenarios 1 and 2 shown in Figures 2 and 3 show the conventional MPC controller to control the production flow and the pump head. These two variables are essential to control, as they directly imply activating the typical envelope constraints in centrifugal pumps. In this control configuration, the liquid level above the pump intake, or the pump suction pressure, must be maintained between maximum and minimum operating limits. This restriction aims to prevent cavitation in the pump and premature degradation.

In scenario 1, the controller starts from a different point of origin and searches for a low flow point. In the second scenario, the controller starts from this low-flow region. The controller automatically captures the difference in initial conditions to update the internal states. In both scenarios, the controller aims to search for a high-flow operating point from the low-flow region and the maximum level. Additionally, the controllers must deal with unmeasured disturbances resulting from temperature variations, which are not controlled in this system, and also from a reduced reservoir flow, which is not measured.

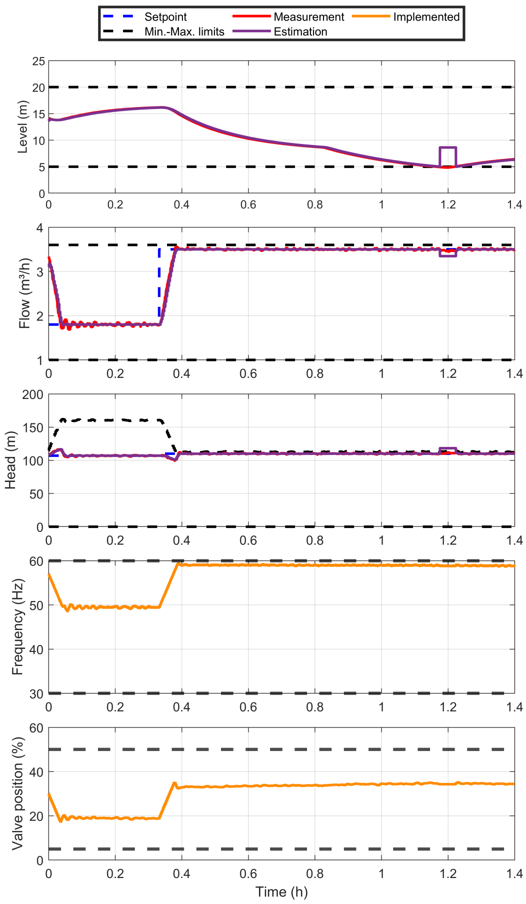

Fig. 2. Standard MPC scenario 01 time responses.

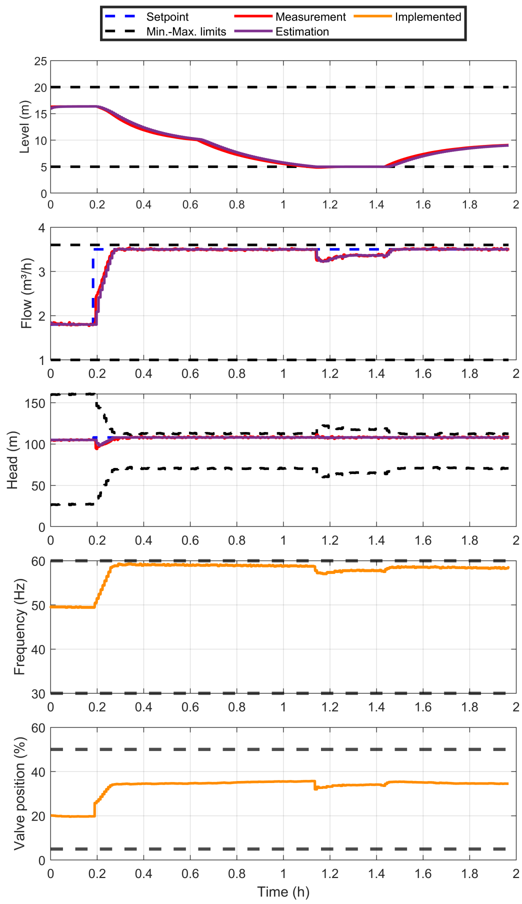

Fig. 3. Time responses standard MPC scenario 02.

In scenario 1, it is verified if the controller can track the flow setpoints. At time 0.8 h of operation, the disturbance in the system's reservoir flow is inserted, which implies a reduction in the level, and the controller begins to compensate for this disturbance to maintain production. When the level reaches the minimum value, the controller becomes unfeasible, as there are no degrees of freedom to compensate for this effect.

In scenario 2, after tracking the maximum flow point and stabilising the operation, the controller must deal with an unmeasured disturbance added to the system in approximately 0.65 h. With the reduction in reservoir flow, the controller must compensate for this disturbance when the level reaches the minimum value. In scenario 2, as shown in Table 1, the frequency and opening variation values were increased so the controller could react quickly and effectively to this disturbance. Given the nature of the disturbance, the controller has to reduce the process flow to compensate for this effect soon. However, it can be observed that the pump head was maintained at the same operating point. This behaviour is important for the ESP pump, as it implies maintaining the equilibrium forces between the pump stages and, as a positive consequence, extends the equipment's useful life.

The zone controller has a more complex and longer test duration. Up to 2 hours into the experiment, the first stage aims to stabilise the plant and bring the input targets to the desired values of 60Hz and 35% opening, a known steady state of the system. Figure 4 shows that this value is not achieved since the flow and head restrictions are activated, preventing the system from operating at 60 Hz. Between 2 and 8.5 hours, the objective was to stabilise the system by increasing the level restriction to 10 to 11 m limits. This implies that the range controller, to avoid infeasibility, will calculate the setpoints within the ESP operation region and will try, through feedback, to bring the plant into this region. The other envelope restrictions were satisfied, and there was no severe violation of the downthrust or upthrust restrictions. In this scenario, for adverse reasons, an unscheduled shutdown occurred at around 4.5 h, but when restarted, the controller could reach the desired values efficiently. After the restrictions were relaxed, between 8.5 h and 13.5 h, the system was directed to achievable targets at the inputs. This caused the controller to stabilise the two manipulated variables and the system to enter a steady state.

Between 13.5 h and 15 h, a restriction was inserted in the flow rate so that the maximum and minimum were equal to 3 m^3/h. This scenario shows how, through the target-MPC controller, it is possible to recover the operation equivalent to the setpoint controller at the outputs. In this case, the production flow rate becomes a setpoint that needs to be tracked by the controller, and the other controlled variables are kept within the limits. After this period, the restrictions were released, and the controller returned to its previous steady state. Viability is ensured in this case, as the controller only needs to maintain the setpoints within

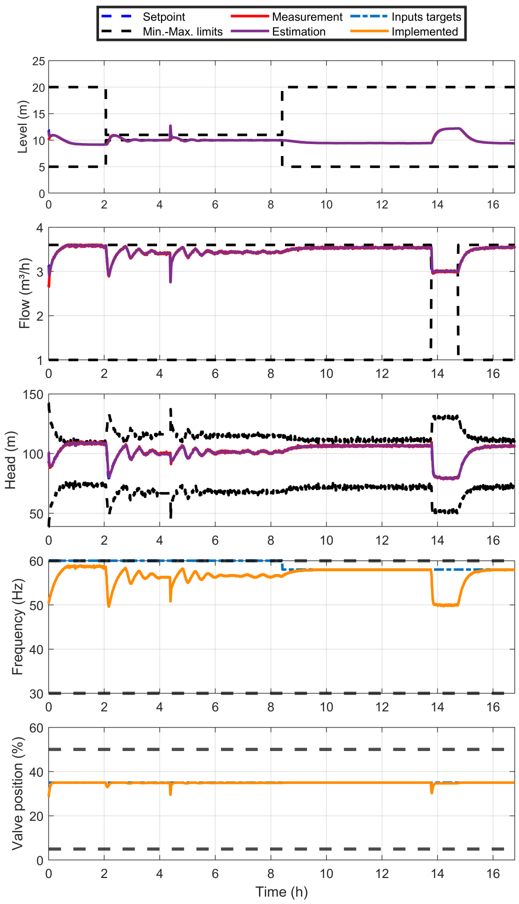

Fig. 4. Time responses target MPC of scenario 03.

Table 1. Tuning parameters, configurations and limits.

Controller	Scnario 1	Scnario 2	Scnario 3
Steady-state	[50 Hz 20%]	[40 Hz 20%]	[50 Hz 25%]
ΔT	30	30	30
Hp	10	15	15
Hc	3	3	3
Qy	[0 1 10]	[0 1 1]	[1 1 1]
R	[1 1]	[0.1 0.1]	[1 1]
Qu			[0.1 0.01]
ΔU_{max}	[0.05Hz 0.05%]	[5Hz 5%]	[1 Hz 1 %]
L_{limits}	[5 20]	[5 20]	variable
$q_{c,limits}$	[1 3.6]	[1 3.6]	variable

the constraints. Similarly, these constraints are applied to the states or predicted output values. In Figures 2 to 4, the graphs depict the actual values measured at the plant, which may momentarily exceed the constraints due to noise and unmodeled disturbances.

Associated with the behaviour observed over time, it is essential to analyse the relationship between the operating envelopes. Some information about the system can be obtained by analysing Figures 5 to 7. The first information is that the controllers can keep the system within the operating envelope with few violations resulting from measurement errors and process noise. This behaviour within the envelope makes seeking an operation that maximises production possible without damaging the ESP. Krishnamoorthy et al. (2019) argues that the region that

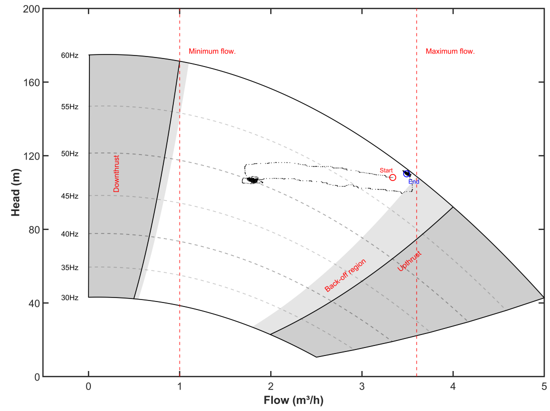

Fig. 5. Standard MPC scenario 01 operational envelope.

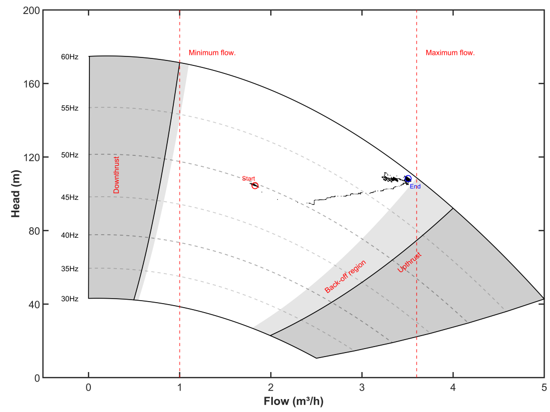

Fig. 6. Operational envelope standard MPC scenario 02.

maximises production is close to the maximum constraints. In the system presented, maximising production implies operating as close as possible to the back-off region or the upthrust region, depending on the risks one wishes to take. The scenario shown defines the back-off region as ten per cent of the maximum and minimum flows.

Specifically regarding the controllers, the results of scenarios 1 and 2, the traditional MPC controller can operate in the maximum flow region. This implies that the controller can move away from the maximum flow zone during dynamic changes. However, the zone controller naturally operates close to the back-off region in a simplified way. This conclusion can be verified in Figures 5 to 7 by the behaviours of the trajectories. In 7

Although they are included in the controller, the head and flow constraints are complementary. This implies that when the head constraint is satisfied, the flow constraint is consequently also satisfied. This is seen in Figure 7. Although the flow constraint is set at 3.5 m^3/h, during operation, the controller follows the limit imposed by the back-off curve, which restricts the flow by limiting the head.

Since it is a controller with a larger domain attraction solution, the range controller is a better field implementation option for the presented scenarios. In systems with a mandatory PID controller in the lowest automation layer, the zone controller can easily send the desired setpoints to the controllers.

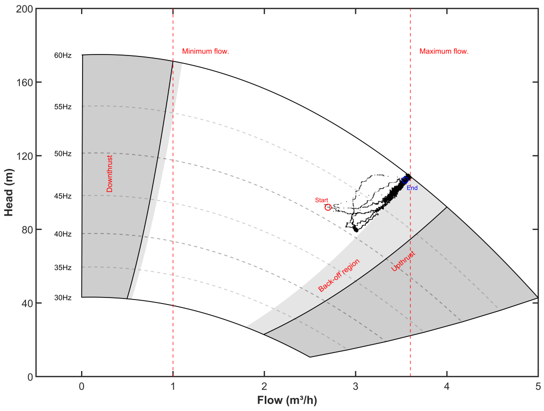

Fig. 7. Operational envelope of target MPC of scenario 03.

From an operational point of view, the control objectives are to keep the valve as open as possible and the frequency at the highest permissible value. The controller tuning is also more straightforward since the Q_y and R matrices can be equal to unity. The Q_u matrix calls attention to the importance of tuning the controller correctly between the two targets, which is weighted so that the controller tolerates more or less the distance between the current value and the specified target.

4. CONCLUSION

This paper presents a practical comparison, challenges and insights into the real-time implementation of MPC controllers in systems operated by electric submersible pumps. Two control approaches were tested. The first is the traditional MPC controller, which can make the solution unfeasible due to its restricted domain of attraction for solutions. On the other hand, the zone-MPC controller has an expanded domain of attraction by using the setpoints of the controlled variables as the decision variable and directing the controlled variables to desired operating points and input targets. The scenarios presented showed that the zone-MPC controller with targets at the inputs could stabilise the system, just like the traditional MPC, and operate at defined output points, in addition to a more secure operation in the production maximisation region.

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