# Optimal Control of Water Quality in a Recirculating Aquaculture System

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**Abstract:** This study compares nonlinear model predictive controls, using setpoint tracking objective function (NMPC), and economic objective function (E-NMPC), with a hierarchical control structure of PI controllers applied to the water treatment of a Recirculating Aquaculture System (RAS), which consists of a tank, a biofilter, a stripper and an oxygen cone. Two of the three control structures used in this work consist of an optimization layer on top of proportional integral (PI) control loops or NMPC. The optimization layer reduces the degrees of freedom with an economic objective function by deactivating some of the manipulated variables when choosing between buffer and base addition and location of addition to the system. The third structure consists of a single layer with E-NMPC. The PI control structure is easy to design once we know the relationship between the variables. The PI controllers' performance were satisfactory, but a small back-off would be needed, if the constraints would not be soft constraints, or use of buffer with base would be necessary to improve speed and avoid constraint violation, as some components took more than 6 days to reach the optimal concentration. The NMPC and the E-NMPC performed better: the NMPC was much faster on conducting the controlled variables to optimal conditions, despite not providing optimal economic cost during the trajectory; and the E-NMPC provided a mixture of smooth trajectory and optimal cost.

*Keywords:* Process control applications, Control of constrained systems, Dynamics and control, Hierarchical multilevel and multilayer control, Optimal operation of water resources systems, Model predictive control of water resources systems

## 1. INTRODUCTION

Aquaculture systems for commercial purposes consists of rearing one or more species of aquatic organisms inshore or offshore. In inshore or offshore closed environments, the focus is usually in rearing only one species, as the conditions are controlled and external contact is avoided. The effluent is significantly large in flow-through systems, which are also called raceways, due to discharge of the entire outflow of the tank (Ridler and Hishamunda, 2001). A modification to raceways are recirculating of treated water, and these processes are called Recirculating Aquaculture Systems (RAS).

Automated RAS, also called as Smart RAS or Intelligent Aquaculture, when artificial intelligence is used, consists of implementing control and optimization solutions to avoid risks and reduced production with as little as possible of human interaction with the system. This is a challenge due to the complexity of the system, but it is less difficult when the system is divided into subsystems: rearing unit, solid and water treatments.

This study is focused on the water treatment part of RAS of Atlantic salmon (*Salmo salar*), which consists of

tanks, a biofilter, a stripper, and an oxygen cone. The system is complex, but it was simplified in previous work (Dos Santos et al., 2022), where the model was developed for control and optimization purposes, the steady state and dynamic behaviors were analyzed, and simple proportional integral control of oxygen and nitrate were implemented. For optimal growth and welfare of the fish, the conditions of the environment are assumed to have a small range, so other controllers are required to keep them within this region.

Other authors applied control and optimization in other RAS configurations, and it includes Wright (2011), Farghally et al. (2014), and Summerfelt et al. (2015). In order to the control and optimization to be successful, one needs to gather information of all the toxic compounds, important water conditions, and all the safety bounds. When the system operates in optimal conditions, one is able to distinguish which constraints affect the optimization directly or indirectly, as they are active or not. The inactive constraints are important to the dynamic optimization to avoid abrupt changes and going too far from optimal steady-state conditions, and the active ones dictate these conditions.

The main contribution of this work is the comparison of nonlinear model predictive control structures with a systematic procedure for control design applied to a water treatment system of recirculating aquaculture systems of Atlantic salmon.

## 2. PROCESS DESCRIPTION

The process consists of a tank, where the fish is reared, and a water treatment system. In the water treatment system, the tank effluent is treated by a biofilter, on which bacteria convert ammonium into nitrate, and a stripper, which removes carbon dioxide from the system. Most of the effluent is recycled back to the tank, and the rest is purged. There are makeup streams of water and oxygen; and other inputs such as air, fanned through the stripper, fish feed, added in the fish tank, and base (NaOH) and/or buffer (NaHCO$_3$), that can be added to the tank or to the biofilter.

The fish feed is considered a disturbance that changes from day to day in a piece-wise constant manner. The fish metabolism is considered to produce ammonia, carbon dioxide and biomass, which is the mass growth of the fish, and their production rate are assumed to be linear functions of the fish feed. In the biofilter, bacteria are considered to transform ammonia (NH$_3$) into nitrate (NO$_3^-$) with a constant conversion. The temperature and salinity are assumed to be constant and equal to 14°C and 15 g/kg, respectively.

The model uses three reactions invariant variables, which are variables that do not change with equilibrium reactions, and these variables are defined as follows:

$$c_{TAN} = c_{NH_3} + c_{NH_4^+} \tag{1}$$

$$c_{TIC} = c_{H_2CO_3} + c_{HCO_3} + c_{CO_3^2} \tag{2}$$

$$c_{alk} = c_{OH} + c_{HCO_3} + 2c_{CO_3^2} - c_{NH_4^+} - c_{H^+} \tag{3}$$

where $c_j$ is the concentration of component j; TAN denotes total ammonia nitrogen; TIC, total inorganic carbon; and alk, alkalinity.

Other differential states are nitrate and oxygen concentrations in the tank and biofilter, and the algebraic states are TIC concentration in the stripper, and pH in all units. The model consists of 14 differential and algebraic equations. More details about the process and model can be found in Dos Santos et al. (2022).

## 3. OPTIMIZATION PROBLEM

### 3.1 Operating constraints

The system must satisfy a few constrains to keep the fish safe, healthy and with optimal growth rate condition. Depending on the species, these constraints differ. Pedersen (2018) exemplifies an optimization of RAS design for Rainbow trout and Atlantic salmon, where it cites different parameters depending on species. As the fish species in this work is Atlantic Salmon, the restrictions for optimal growth rate and safety regarding $w_i$, which is the mass concentration of component $i$, pH, and alkalinity are given as follows:

- Carbon dioxide:
$$w_{H_2CO_3}^T \leq 15mg/L$$
- Nitrate:
$$w_{NO_3}^T \leq 100mg/L$$
- Ammonia:
$$w_{NH_3}^T \leq 20\mu g/L$$
- pH in the tank:
$$7 \leq pH^T \leq 7.5$$
- pH in the biofilter:
$$7 \leq pH^B \leq 8$$
- Alkalinity in the tank:
$$w_{alk}^T \geq 50mg(CaCO_3)/L$$
- Alkalinity in the biofilter:
$$w_{alk}^B \geq 50mg(CaCO_3)/L$$

There are also some operating constraints regarding oxygen mass concentration, $w_{O_2}^T$, recirculating volumetric flow rate, $q$, and maximum amount of air being ventilated through the stripper, $\dot{V}_{air}$.

- Oxygen concentration:
$$80\% \times w_{O_2,sat} \leq w_{O_2}^T \leq 120\% \times w_{O_2,sat}$$
where $w_{O_2,sat}$ is the mass concentration of oxygen in water at saturation.
- Recirculating volumetric flow rate:
$$5m^3/min \leq q \leq 50m^3/min$$
- Air flow rate:
$$\dot{V}_{air} \leq 5q_{max}$$

### 3.2 Economic Objective Function

A general optimization problem is given by

$$\min_{\boldsymbol{x},\boldsymbol{z},\boldsymbol{u}} J(\boldsymbol{x},\boldsymbol{z},\boldsymbol{u}) \tag{4}$$

$$\begin{aligned} \text{s.t.} \quad & \dot{\boldsymbol{x}} = s_d(\boldsymbol{x},\boldsymbol{z},\boldsymbol{u}), \\ & s_a(\boldsymbol{x},\boldsymbol{z},\boldsymbol{u}) = 0, \\ & g(\boldsymbol{x},\boldsymbol{z},\boldsymbol{u}) \leq 0, \\ & \boldsymbol{x}(0) = \boldsymbol{x}_0 \end{aligned}$$

where functions $s_d$ and $s_a$ are the differential and the algebraic equations, respectively, g is the set of inequality constraints mentioned in the previous subsection, and $x_0$ is the initial condition.

As the model does not take the effect of water quality on the fish growth into consideration, the cost of the plant, S, which is also the function J to be minimized in a steady-state economic optimization in each step $k$, is purely given by the operating cost, given by Eq. 5. In the case of a dynamic economic optimization, J becomes S plus the regularization term, as shown in Eq. 9, in the next section.

$$\begin{aligned} J = S(\mathbf{u}_k) &= p_1(1-r)q^B + p_2 \, \dot{m}_{air} + p_3 \sum_{i=T,B} \dot{m}_{base}^i \\ &+ p_4 \sum_{i=T,B} \dot{m}_{buffer}^i + p_5 \, q^m + p_6 \, q \end{aligned} \tag{5}$$

where p$_j$ with $j = 1, 2, ..., 6$ are prices of operation of vacuum and exhaustion fans (Nistad, 2018); base (Tianjin

Table 1. Price of each input

| Variable | Value | Unit | Description |
|----------|-------|------|-------------|
| $p_1$ | 19.19 | NOK/m$^3$ | Effluent disposal |
| $p_2$ | 5.71e-05 | NOK/mol | Vacuum and Exhaustion fans |
| $p_3$ | 0.102 | NOK/mol | NaOH flakes |
| $p_4$ | 0.148 | NOK/mol | NaHCO$_3$ powder |
| $p_5$ | 14.17 | NOK/m$^3$ | Makeup water |
| $p_6$ | 1.87e-02 | NOK/m$^3$ | Pump operation |

Chengyuan Chemical CO. LTD, 2021); buffer (Farmasino CO. LTD, 2021); makeup water, which is assumed to have the same price as fresh water; effluent disposal (Trondheim kommune, 2021); and standard pump operation, respectively, described in Table 1, assuming that the prices do not change during the operation.

## 4. CONTROL DESIGN

A summary of all structures is presented in Fig. 1. Case A consists of an upper layer with a steady-state optimization, a middle layer with a Split-range block, and a down layer with PI control. Case B consists of an upper layer with a steady-state optimization, and a down layer with nonlinear model predictive control (NMPC). And finally, Case C consists of a single layer with economic model predictive control (E-NMPC).
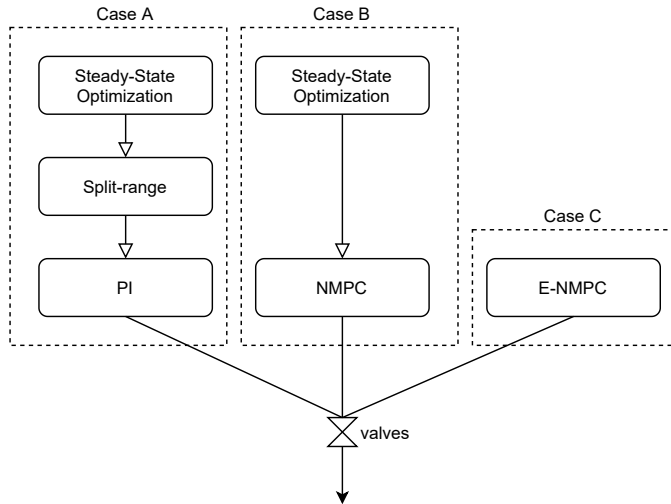


Fig. 1. Control structures

Another point is that the disturbance changes as piecewise constant dependent on day of operation, so the system needs to be optimized daily for Cases A and B.

The simulation of the plant, which is represented by a first-principle model of the water treatment of RAS, uses IDAS method from SUite of Nonlinear and DIfferential/ ALgebraic Equation Solvers (SUNDIALS), distributed along with CasADi v3.5.5 for Python v3.8.8.

### 4.1 Case A

After formulating the optimization problem, the next steps are to optimize using Eq. (4) and (5) for expected disturbances, and implement optimal operation, defining what to control.

Based on the optimization result, the active constraints dictate the most important variables to be controlled, and its setpoint becomes the restriction value that was reached. The optimization also defines the location of base/buffer addition. In order to pass this optimal decision to the regulatory layer, a split-range block must be put in between to activate or deactivate the base/buffer addition, depending on type and location.

In Dos Santos et al. (2022), we showed that it is essential to control oxygen and nitrate concentrations. Based on that, the oxygen and the nitrate pairings are set, but process knowledge needs to be used to suggest other pairings. A systematic procedure is conducted for the remaining pairs to be defined.

*Model identification:* First, the system is identified as first order plus time delay (FOPTD) models. To achieve that, a step change is applied in one manipulated variable ($u_k$) at a time, and the identification of the dynamic responses is executed using the Scipy package in Python, minimizing the integral of the absolute magnitude of the error (IAE), subject to bound constraints, and described by Eq. 6.

$$\min_{\boldsymbol{t}, \boldsymbol{y}, k, \tau, \theta} \int_0^{t_f} |error(\boldsymbol{t}, \boldsymbol{y}, k, \tau, \theta)| dt \qquad (6)$$

$$\text{s.t.} \quad \theta \geq 0,$$
$$\tau \geq 0$$

where *error* is the error function described by Eq. 7 dependent on time, $\boldsymbol{t}$, gain, $k$, time constant, $\tau$, and time delay, $\theta$; $\boldsymbol{y}$ is the dynamic response vector; $t_f$ is the duration of the dynamic response.

$$error(\boldsymbol{t}, \boldsymbol{y}, k, \tau, \theta) = k(1 - \mathrm{e}^{-(\boldsymbol{t}-\theta)/\tau}) - \boldsymbol{y} \qquad (7)$$

*Closing the control loops:* After all pairings are set, the control loops are closed one by one, and the identification is re-executed every time one loop is closed. The order of the closure is told by prior knowledge of the system on how intense one input variable can affect the other controlled variables besides its pair.

Finally, the SIMC rules (Skogestad, 2003) (Skogestad's PID settings) for systems described by first order plus time delay transfer functions are used to tune the controllers.

### 4.2 Cases B and C

When letting the algorithm to decide the location of addition of base/buffer, this decision can be added to a nonlinear model-based predictive control. In order to solve the minimization problem of the model predictive control, the integration method needs to be chosen carefully. For this system, which has a measured disturbance that varies from day to day, the integration method single shooting is not advised, and multiple shooting increases a lot the computation time. Therefore, the method direct collocation was used, and set to have one intermediate collocation point and to use a third degree polynomial to interpolate within each control interval.

The objective function to be minimized is given as follows:

**Case B**) Setpoint Tracking:

$$J = \sum_{k=0}^{N-1} \left[ ||\boldsymbol{x}_k - \boldsymbol{x}_{opt}||_Q^2 + ||\boldsymbol{u}_k - \boldsymbol{u}_{k-1}||_R^2 \right]$$
(8)

where N is the ratio between control horizon and control interval; Q and R are diagonal matrices of dimension $nx \times nx$, and $nu \times nu$, respectively, $nx$ is the number of differential states, $\boldsymbol{x}$, and $nu$ is the number of manipulated variables, $\boldsymbol{u}$; $x_{opt}$ is the optimal steady state for the differential states, given by the upper layer; $||\boldsymbol{u}_k - \boldsymbol{u}_{k-1}||_R^2$ is the penalty of change in the manipulated variables, also called regularization term.

**Case C**) Economic Dynamic Optimization:

$$J = \sum_{k=0}^{N-1} \left[ S(\boldsymbol{u}_k) + ||\boldsymbol{u}_k - \boldsymbol{u}_{k-1}||_R^2 \right] \quad (9)$$

where S is the cost function given by Eq. (5).

## 5. RESULTS AND DISCUSSION

### 5.1 Steady-state Optimization

With the optimization problem defined in Section 3, the steady-state optimization can be easily done. The results for the first day of the production are presented in Tables 2 and 3.

Table 2. Optimal operation data on day 1

| Variable | Value | Unit |
|---|---|---|
| $\dot{m}_{air}$ | 1074.71 | mol/min |
| $r$ | 0.9 | - |
| $\dot{m}_{O_2}$ | 11.36 | mol/min |
| $\dot{m}_{base}^T$ | 4.21 | mol/min |
| $\dot{m}_{base}^B$ | 1.21 | mol/min |
| $\dot{m}_{buffer}^T$ | 0.0 | mol/min |
| $\dot{m}_{buffer}^B$ | 0.0 | mol/min |
| $q$ | 9.07 | m³/min |

Table 3. Optimal steady-state values for some variables on day 1 [mmol/L or -]

| Variables | Tank | Biofilter | Stripper |
|---|---|---|---|
| $c_{alk}$ | 4.32 | 3.85 | 3.85 |
| $c_{TIC}$ | 4.74 | 4.27 | 4.04 |
| $c_{H_2CO_3}$ | 0.27 | 0.43 | 0.21 |
| $c_{TAN}$ | 0.18 | 4.91e-03 | 4.91e-03 |
| $c_{NH_3}$ | 8.09e-04 | 1.21e-05 | 2.40e-05 |
| $c_{NO_3}$ | 1.61 | 1.61 | 1.61 |
| $c_{O_2}$ | 0.35 | 1.01e-06 | 1.01e-06 |
| $pH$ | 7.26 | 7.0 | 7.3 |

The optimization results in Table 2 indicate that either base or buffer is added to a specific unit. However, manipulating the price of buffer, this could change, as illustrated in Fig. 2 in the region in the middle (between 0.005 and 0.04 NOK/mol, approximately). The figure illustrates the trade-off between price and process requirement, and shows a range of buffer prices that activates the upper bound constraints of alkalinity and/or TIC concentration

(range between 0 and 0.005 NOK/mol, approximately); a second region in the middle, where base is added in the tank, and buffer is added in the biofilter, referenced in this work as Case A.1; and a third region with only base being used, referenced as Case A.2. The current price of buffer lies at the third region, as seen in Table 1.
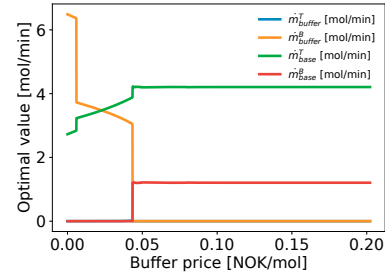


Fig. 2. Buffer price sensitivity

Table 4 shows the operating constraints converted to the units of the system to better visualization. Comparing it with Table 3, we can see that the constraints are active for $c_{O_2}^T$ and $c_{NO_3}^T$, so they are chosen to be controlled variables. The other controlled variables are defined using process knowledge.

Table 4. Upper and lower constraints [mmol/L or -]

| Lower bound | Variables | Upper bound |
|---|---|---|
| 0.50 | $c_{alk}^T$ | - |
| 0.50 | $c_{alk}^B$ | - |
| 0 | $c_{H_2CO_3}^T$ | 0.34 |
| 0 | $c_{NH_3}^T$ | 0.0012 |
| 0 | $c_{NO_3}^T$ | 1.61 |
| 0 | $c_{O_2}^T$ | 0.2348 |
| 7.0 | $pH^T$ | 7.5 |
| 7.0 | $pH^B$ | 8.0 |

### 5.2 PI Control Design

In order for the fish to have optimal growth rate, the environment is required to satisfy a few constraints. Besides oxygen and nitrate concentrations, other restricted variables have direct correlation with input variables, such as ammonia concentration, which depends on TAN concentration and pH; carbon dioxide, which depends on TIC concentration and pH; and pH, which is defined by alkalinity, TAN and TIC concentrations.

To reduce the amount of controllers and reduce nonlinearity of relationship between MV and CV, alkalinity, TAN, and TIC concentrations are studied to be substitutes for direct controls of carbon dioxide, ammonia and pH. TAN concentration in the biofilter is defined by the biofilter efficiency, which is considered constant, TAN concentration in the tank, which depends linearly on the fish feed according to the fish metabolism assumption, and the liquid flow rate, q, which dictates how fast the water treatment is. Therefore, TAN concentration in the tank needs to be controlled and its pair should be q, as the fish feed is a disturbance.

Alkalinity and TIC concentrations (in the tank and in the biofilter) can be controlled by the MVs left: amount of base or buffer added in the tank and in the biofilter, and amount of air used at the stripper. TIC concentration in the biofilter just changes with TIC concentration in the tank, recirculating volumetric flow rate, q, makeup water and air inlet. Therefore, one of the TIC concentrations need to be controlled by the air inlet, and the closest one from the stripper is TIC concentration in the tank.

The bounded optimization solved to identify the responses was very sensitive to the initial guess. Therefore, the dynamic response graphs are important to set good initial guesses. Using the knowledge from the process acquired in previous work and choosing the closest pair, the pairing is chosen as in Table 5, although controller using buffer is deactivated on day 1, but it can be activated as needed by the Split-range block.

The order of closing the loops affect the difficulty on controlling the system, meaning that some CVs are coupled with more than one manipulated variable, as expected, but this problem can be bypassed if the loops that affect other variables the most are closed before. The order of closure of the loops, and the tuned $\tau_C$, which is a vector of the variables to be tuned in each control when using the SIMC rules, are also shown in the table below.

Table 5. Suggested pairing and tuning parameter

| MV | CV | $\tau_C$ |
|---|---|---|
| $\dot{m}_{O_2}$ | $c_{O_2}^T$ | 15.46 |
| $r$ | $c_{NO_3}^T$ | 22.25 |
| $q$ | $c_{TAN}^T$ | 1000.0 |
| $\dot{m}_{base}^T$ | $c_{alk}^T$ | 645.38 |
| $\dot{m}_{base}^B$ | $c_{alk}^B$ | 153.72 |
| $\dot{m}_{buffer}^T$ | $c_{alk}^T$ | - |
| $\dot{m}_{air}$ | $c_{TIC}^T$ | 1900.0 |

### 5.3 Dynamic Simulation with PI controllers

The system has 8 dynamic degrees of freedom, but with the optimization results, 2 controllers are deactivated due to Case A.2 being activated by the optimization layer. Therefore, 6 controllers need to be active.

Fig. 3 shows the main dynamic responses to step changes in disturbance with only oxygen being controlled. Almost all variables violate the constraints, leading to the fish to suffer, causing non-optimal growth or death. Fig. 4 shows the main MVs and CVs' dynamic responses to the same disturbance step changes. From this figure, it can be seen that some CVs take more than 6 days to reach the setpoints, and the controller could have not been any faster due to abrupt changes and constraint violation of other variables, such as pH. Alternatively, a small back-off would be needed, or to use buffer at the beginning, when there is a need for abrupt increase on base intake. The latter alternative could lead the system to optimal conditions quicker, as the pH would not violate the constraints and alkalinity would increase faster with more base/buffer.

Overall, the closed loops performed well and the entire system was driven to optimal steady-state condition eventually.
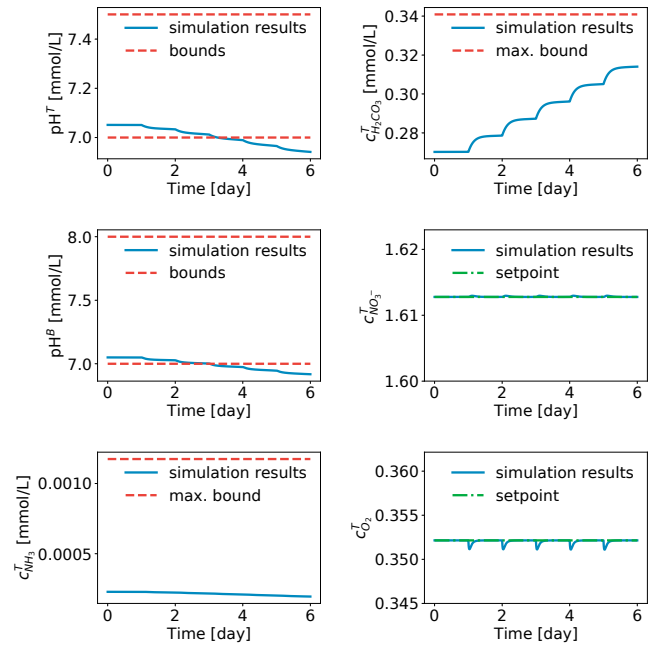


Fig. 3. Dynamic behavior of the process with oxygen and nitrate controls, and subjected to disturbance, F
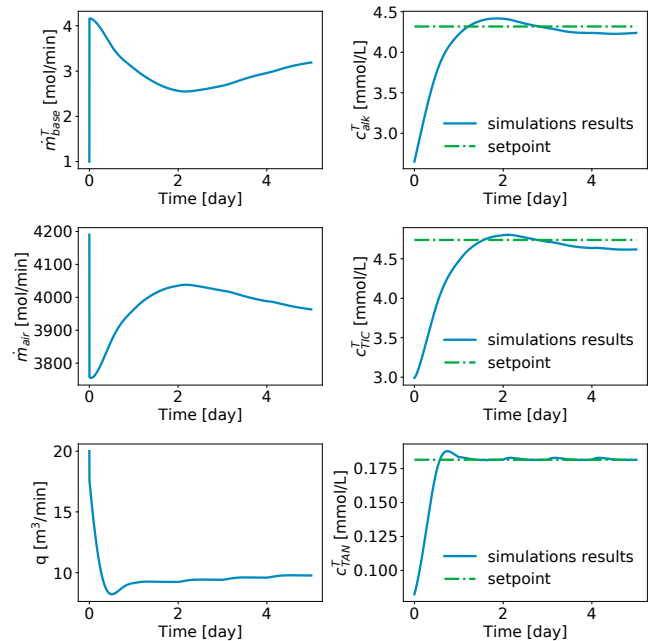


Fig. 4. Dynamic behavior of the process with all 6 PI controllers, and subjected to disturbance, F - MVs on the left column and CVs on the right column

### 5.4 Model Predictive Control comparison

Two different objective functions for the optimal controllers were used: setpoint tracking and economic objective function, described by Eq. (8) and (9), respectively. The tuned diagonal matrices Q and R are given as follows:

$$Q = diag(1e2, 1e2, 1e3, 1e3, 1e2, 1e2, 1, 1, 1, 1)$$
$$R_{\text{NMPC}} = diag(1e-3, 1e3, 1e2, 1e2, 1e2, 1e2, 1e2, 1e2)$$
$$R_{\text{E-NMPC}} = diag(1e-7, 10, 1, 1e-3, 1e-4, 1e-4, 1e-4, 10)$$

Fig. 5 shows the closed loop response with control horizon of 24 hours and control interval of 20 minutes, for both the MPCs. The NMPC conducted all controlled variables to their optimum values plus algebraic variables in a really short time (less than a day). The E-NMPC performed well also, although it took more time for the CVs to reach optimal steady-state value.
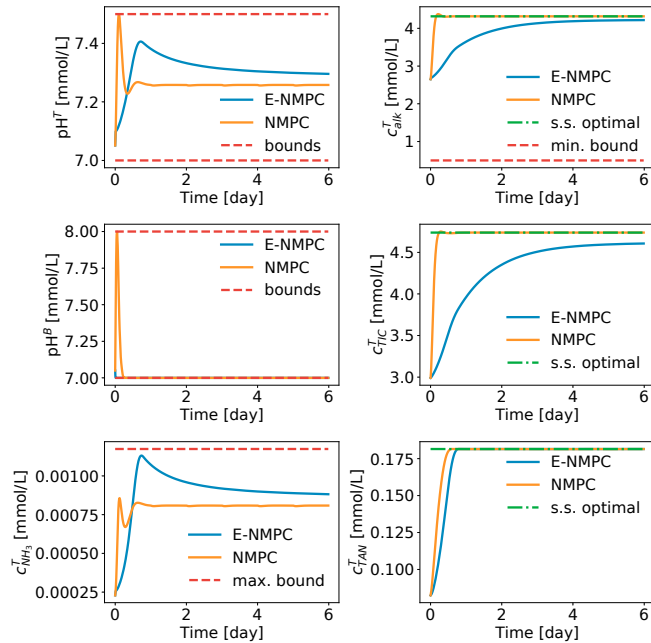


Fig. 5. Dynamic behavior of the process with MPCs and subjected to disturbance, F

## 6. CONCLUSION

The volume of the different RAS units are big, except for the stripping column, so the time constant of the entire process is high. On the other hand, the disturbance can lead the process to infeasibility, if no control is done. To speed up the process and avoid infeasibility, a control structure is needed.

In this work, we have presented a comparison of three optimal control structures. Two of them are hierarchical control structures, where an optimization layer calculates the optimal setpoint. In Case A, after the optimization layer, a split-range block handles the switch between manipulated variables. In Case B, the optimization layer gives the optimal setpoint directly to a nonlinear model predictive controller. In Case C, the structure is a single block consisting of an economic model predictive control, led by an economic objective function.

All the control structures gave a satisfactory performance, driving the system to the optimal steady-state conditions. The PI control structure depends on how far from optimal the system is at the beginning to drive it faster to optimal conditions, as it took more than 6 days to reach optimality.

To make the PI controllers faster, buffer would be needed, which means that it would cost more, as buffer is more expensive than base, according to the current prices. The E-NMPC provided a trajectory that is economically optimal, but it achieves a different steady-state optimal. On the other hand, the NMPC provided a dynamically optimal trajectory, but also economically non-optimal, as it uses buffer and base. Comparing NMPC with the PI controllers, the NMPC performance was faster on conducting the system to optimal steady-state condition, as it uses buffer and base. The trade-off between speed and cost is evident, but E-NMPC gave the best trajectory, conducting the system to a optimal condition with lower cost.

All the control structures were designed and tested using computational simulations and the model presented in previous work. Therefore, an implementation of these structures controlling the system with growth rate variation and addition of noise is suggested to evaluate the effect of model mismatch on the results.

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