Diseño de una estrategia de Control Predictivo basado en Modelo (MPC) para una Planta de Desalinización en un entorno Hardware in the Loop (HIL)

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Design of a Model Based Predictive Control (MPC) Strategy for a Desalination Plant in a Hardware in the Loop (HIL) Environment.

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Abstract. The desalination process using the reverse osmosis technique is important for the production of drinking water, but its control is a great challenge due to its nonlinear and multivariable nature. In academia, the implementation of physical industrial processes represents a considerable cost, taking this into account, in recent years the technology has evolved and boomed called the "metaverse", where it is proposed to create a virtual representation of reality. This research work proposes a hardware-in-the-loop (HIL) environment which consists of a virtual reverse osmosis industrial process and designs and implements the control algorithm in a programmable logic controller (PLC), which is common in the industry. The system is versatile to implement different control algorithms and opens the door to the use of different control devices for its implementation. The design methodology to be used consists of three sections. The first section is the mathematical model of the industrial process. The second section is the implementation of the virtual process in Unity3D software. The third section is the implementation of two control strategies: Proportional Integral Derivative Control (PID) and Model-Based Predictive Control (MPC). Finally, a comparison of the performance of the implemented controllers for both the permeate flow variable (F) and conductivity (C), in transient and steady state, is performed.

Keywords: Hardware in the Loop, advanced control, PID, virtual laboratory, reverse osmosis.

1 Introduction

At present, almost 700 million people in 43 different countries suffer from a lack of water, and the problem is even worse in the future since it is estimated that by 2025, 1.8 billion people will have absolute water shortages and two-thirds of the world's population will be living under water stress [1]. What is worrying is that, after decades of efforts to address the situation, these figures are still very high [2][3]. Seawater desalination appears as a viable solution for the population, which consists of extracting clean, pure, and ready-to-drink water.

Desalination is declared as the separation of salt from a substance, economically it favors the drinking water companies of each country, being for some countries their only source of obtaining this liquid, for this, several techniques help to separate the water from the salt which is: distillation, freezing, flash evaporation, electrodialysis, thermal de-application and reverse osmosis, the latter being the most widely used in desalination processes, due to its benefits such as high water purity and use of ocean water [4][5].

Reverse osmosis desalinization plants generally use traditional controllers, which do not ensure efficient performance in the transient state of the variables to be controlled in the process, causing clogging in the membranes and thus higher energy consumption, lowering permeate production and reducing its quality. There are several traditional controllers used for the reverse osmosis process, for example, the PI and PID controller using the Ziegler-Nichols tuning method which shows that the flow output has overshoot [6] [7], this could be improved with the use of more sophisticated controllers, such as model-based predictive control (MPC), such as model-based predictive control (MPC), used for example in a horizontal three-phase separator [8], a horizontal two-phase separator [9]. Another controller implemented is the fuzzy controller using a pilot plant in the R&D laboratories, concluding that fuzzy controllers prove to be more efficient than traditional PI and PID controllers in steady-state error and the more damped response of the manipulated variables [10], also used for a combined cycle thermal power plant [11] and flow processes[12].

Therefore, the design of control strategies to optimize the reverse osmosis process and operate efficiently in the face of changes in influent water quality and changes in the plant's operating environmental conditions is important. In addition, the aim is to achieve plant profitability and compliance with product quality standards while being environmentally responsible and seeking to maximize profits by optimizing existing processes. This can be achieved with the design of advanced control algorithms, which in this work is designed (MPC). These controls have the following advantages: increased product profitability, reduced energy consumption, increased information flow in the system, improved product quality and consistency, reduced waste, increased system response speed, improved process safety, and reduced environmental emissions [13].

Over time it has been concluded that the so-called advanced controllers have better performance than PI or PID controllers, especially for MIMO processes, from control in oil refineries [14], to water treatment, since the controllers are becoming more sophisticated according to the needs of the industry. Normally, advanced controllers are not implemented in these devices (PLC), since the manufacturer's software does not allow it or does not have simple tools for its implementation. In addition, for the design of advanced control is necessary, knowledge in this area and therefore learning time for development. Therefore, among the new technological tools, which have a strong impact on today's society, is virtual reality, such as the virtual workstation for level and temperature process control [15], which stimulates students in the learning process and encourages interest in exploring things more attractively compared to the typical teaching concept of the last decades, that is why 3D virtual environments are evolving exponentially, due to their great usefulness in the work field as well as in the academic field [16], allowing the development of a plant similar to reality. However, these industrial processes being virtual will have an ideal environment which does not happen in practice, considering this, the controllers are implemented in a physical industrial control device within the simulation loop. [17].

In this research project, a HIL environment is designed for an industrial reverse osmosis desalination process, controlled by a programmable logic controller (PLC). There is the ability to connect to other devices by coupling the communication between the virtualized plant and the control device. A comparison is made between advanced and traditional control versus multivariable industrial processes. It provides the following contributions: i) A realistic linear MIMO model of an industrial desalination process, ii) The design of an MPC control for a MIMO desalination process, iii) A methodology to implement the MPC control in a physical industrial control device.

2 Reverse Osmosis Process

This section describes the operation and analysis of the industrial reverse osmosis process.

2.1 Description of Reverse Osmosis Process Operation

The operation of the industrial reverse osmosis process is explained with the piping and instrumentation diagram (P&ID), which details the instrumentation and equipment (see Fig. 1).

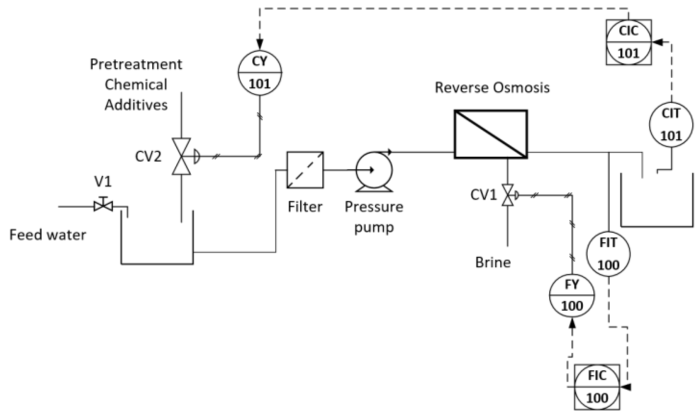

Fig. 1. Reverse osmosis process P&ID diagram.

The reverse osmosis process (See Fig. 1), includes a constant water input, and the desalination process includes two control loops: 100 and 101. The control loop 100 is to control the permeate flow which starts by taking the permeate flow reading through a flow indicator transmitter (FIT-100), whose signal enters the flow indicator controller (CIF-100), the output of the flow controller passes through an electric to the pneumatic signal converter (FY-100) and reaches the actuator which is a control valve (CV1). Loop 101 is responsible for controlling the conductivity of the permeate flow and requires a conductivity indicator transmitter (CIT-101), whose signal enters the conductivity indicator controller (CIC-101), the output goes through an electrical to a pneumatic signal converter (CY-101) which is connected to the actuator which is a control valve (CV2).

Osmosis is a natural process that occurs in plant and animal tissues. It can be said that when two solutions of different concentrations (composed of a solvent and a solute dissolved in a solvent), are joined by a membrane that allows the passage of the solvent, but not a solute, there is a natural circulation of solvent through the membrane, minus the solution. The height difference obtained is converted into a pressure difference, called osmotic pressure. However, concerning the solution, an external pressure greater than the osmotic pressure of the solution is applied. On the other hand, the process can be reversed, recycling the solvent from a more concentrated solution to a solution with a lower concentration will eventually yield water of acceptable purity. [18]. In membrane separation processes, the solute to be separated accumulates on the membrane surface due to concentration polarization (solute retained in the membrane) or fouling phenomena (such as pore clogging, adsorption, etc.) [19]. For this reason, both the pressure and the pH supplied to the membrane must be controlled, thus extending its useful life. For this, at the beginning of the process, the pH is regulated by adding sulfuric acid or hydrochloric acid, and the pressure by throttling the valve (CV1) that controls the pressure exerted on the membrane.

2.2 Mathematical Model

Several theoretical models of reverse osmosis membranes have been developed over the past decades. When developing a theoretical model to predict the performance of a reverse osmosis membrane, one of the first aspects to consider is the selection of a transport model that describes the flow of water and salt through the membrane [20]. Although most reverse osmosis models use process identification and obtain plant dynamics, this only corresponds to a SISO model. Others take into account the mass balance and the concentrations of the inflow and outflow, there are some models that due to the computational time are not able to simulate the process in real-time [21], based on the above and the comparative study carried out in [22]. In this research work, we use the model described in [23] (see Fig. 2), because it represents a real plant with relation to the influence of pH on the quality of permeate obtained from the reverse osmosis process, using real data from a laboratory plant. The model [23] is multivariable and uses feed water pressure and pH as manipulated variables, and the variables to be controlled are permeated flow and conductivity.

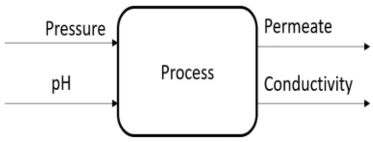

Fig. 2. Reverse osmosis process input and output diagram

The dynamic model of the plant obtained is described by equations (1) and (2), where the inputs of the reverse osmosis process (U) are pressure and pH. The outputs (Y) are permeated flux and conductivity, where $\mathrm{G_p}$ are the gains: (3) shows the transfer function relating permeate flux (F) to pressure (P). Equation (4) is zero since the relationship that exists between the pH input does not affect the permeate flux, (5) similarly relates the conductivity (C) to the pressure exerted on the membrane, and (6) the transfer function of conductivity (C) to pH. The model described above serves for the implementation of the HIL, since it has the dynamics of the real process variables. It should be noted that to implement this model in the virtual environment it must be in the time domain, so the inverse Laplace transform is applied. [24].

$$Y = G_p U \tag{1}$$

$$\begin{bmatrix} F \\ C \end{bmatrix} = \begin{bmatrix} G_{p11} & G_{p12} \\ G_{p21} & G_{p22} \end{bmatrix} \begin{bmatrix} P \\ pH \end{bmatrix} \tag{2}$$

$$\frac{F}{P} = G_{p11} = \frac{0.002(0.56s+1)}{0.003s^2+0.1s+1} \tag{3}$$

$$\frac{F}{pH} = G_{p12} = 0 \tag{4}$$

$$\frac{C}{P} = G_{p21} = \frac{-0.51(0.35s+1)}{0.213s^2+0.7s+1} \tag{5}$$

$$\frac{C}{pH} = G_{p22} = \frac{-57(0.32s+1)}{0.6s^2+1.8s+1} \tag{6}$$

3 HIL Environment Design for the Industrial Reverse Osmosis Process

La Hardware in the Loop simulation is a well-established technique used in the design and evaluation of control systems. The idea of HIL simulation is to add a part of the real hardware into the simulation loop. Instead of testing the control algorithm on a purely mathematical model of the system, the real hardware (if available) can be used in the simulation loop [17]. Using such a technique connects the actual signals from the controller to a test system to a computer, which has a virtual representation of the plant developed in Unity 3D software. Such software allows the creation of realistic 2D and 3D environments, and control applications, which can be used for educational purposes of industrial processes due to the creation of immersive experiences in environments that are heard more frequently today due to the development of what is known as 'metaverse'.

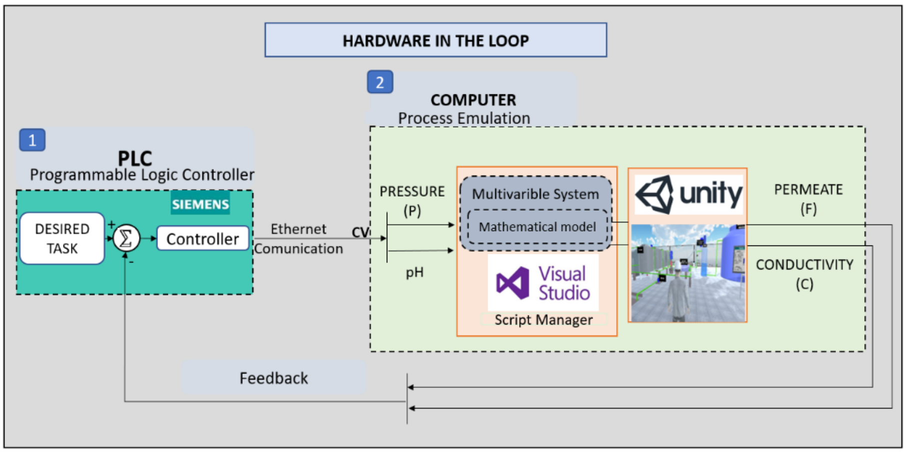

Fig. 3. Hardware in the Loop reverse osmosis process system.

HIL (see Fig. 3) consists of two stages, stage 1 corresponds to a Programmable Logic Controller (PLC), where the control algorithms are programmed, which can be PID, MPC, and others, using the TIA Portal programming software for the PLC S7-1200 AC/DC/RLY and uploading the program to the device. There is also the possibility of using any control device by coupling the communication with the virtualized environment. On the other hand, stage 2 is the virtualized industrial process; communication is via Ethernet. In the first stage, the desired values (SP) and the values of the flow and conductivity variables at that instant are taken, these enter the PLC, then provides the control values (CV) that are sent by Ethernet communication to the second stage, in which is the mathematical model of section 2.2 implemented through lines of Visual Studio 2019 code in Unity 3D, the control values excite the plant making it evolve by modifying the process variables (PV) and these are sent back to the first stage to close the control loop.

The virtualized reverse osmosis process is based on a piping and instrumentation diagram (P&ID) of a real plant (see Fig. 1). For the modeling of the instruments in a virtual way (CAD), it is implemented with the help of software such as Autocad Plant 3D, SketchUp, Blender where the instrumentation involved in the reverse osmosis process is designed. The files are converted into .fbx format to later import them into the Unity 3D software, placing each one in its respective place as close to reality as possible. The mathematical model implemented in Visual Studio 2019 interacts with the environment developed in Unity 3D and this process works together with the physical control device (PLC).

4 Reverse Osmosis Process Control Algorithms Design

After having designed and validated the virtual plant, we proceed to incorporate the controllers.

4.1 PID Control Strategy Design

The control law is defined by equation 7

$$u(t) = K_p \left[e(t) + \frac{1}{T_i} \int_0^t e(t)\,dt + T_d \frac{de(t)}{dt} \right] \tag{7}$$

Where $u(t)$ is the control value, K_p is the gain, T_i is integral time, and T_d is the differential time. The tuning method to be used is Aggressive Lambda tuning. Where this tuning is a special case of pole assignment that is frequently used in the process industry, this is for a FOTD model, where the controller performance is influenced by the parameter selection [24]. For the reverse osmosis process, two PID control loops are implemented, one for the flow variable and one for conductivity, as shown in the closed-loop reverse osmosis industrial process diagram (see Fig. 4).

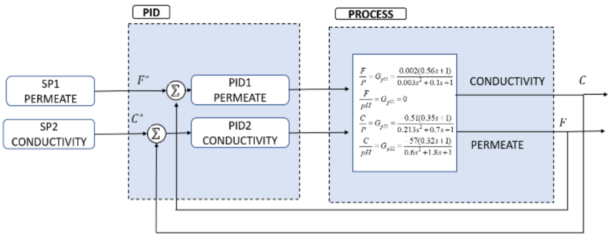

Fig. 4. PID control loop for industrial reverse osmosis process.

4.2 Control design based on the MPC model

For the design of the MPC control it is needed: a prediction horizon, a control horizon, an objective function, restrictions, error weights and control actions [25] [26]. This in turn relies on the plant model to predict the future values of the variables to be controlled as in this case are the permeate flow and conductivity minimizing their errors $(F^*\text{-}F(t))\,y(C^*\text{-}C(t))$. Depending on the weights, the control actions are more aggressive or soft (see Fig. 5).

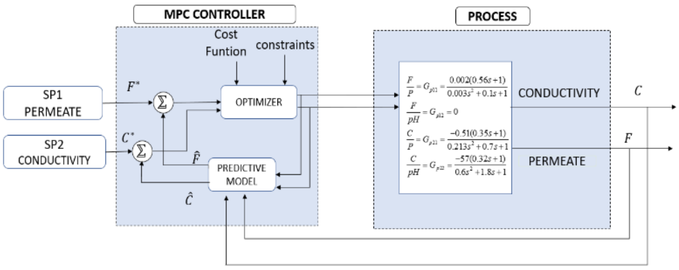

Fig. 5. MPC control loop for industrial reverse osmosis process

An objective function $J(k)$ defined in equation (8) is responsible for minimizing the errors, where the first term $\left[\hat{F}\left(k+i|k\right)-F^*\left(k+i|k\right)\right]^2$ is the squared error between the desired value and the predicted value of the permeate to minimize permeate flow errors, $\delta_1(k)$ which is the weight for the first control target. The second control objective is to minimize the conductivity error $\left[\hat{C}\left(k+i|k\right)-C^*\left(k+i|k\right)\right]^2$ with the corresponding weight $\delta_2(k)$. Subsequently, control objectives are included that minimize the changes in control actions to protect the actuator, therefore, the objective function includes $\left[\Delta u_1\left(k+i-1\right)\right]^2$, which is the variance of the quadratic control value for the permeate control variables, is the weight for the control targets, likewise for $\left[\Delta u_2\left(k+i-1\right)\right]^2$, with its respective weight $\lambda_2(\mathrm{k})$. Where k represents a sample, N_p is the prediction horizon, and N_c is the control horizon.

$$J(k)=\sum_{i=N_f}^{N_p}\delta_1(k)\left[\hat{F}\left(k+i|k\right)-F^*\left(k+i|k\right)\right]^2+\delta_2(k)\left[\hat{C}\left(k+i|k\right)-C^*\left(k+i|k\right)\right]^2+ \\ \sum_{i=0}^{N_{c-1}}\lambda_1(k)\left[\Delta u_1(k+i-1)\right]^2+\lambda_2(k)\left[\Delta u_2(k+i-1)\right]^2 \tag{8}$$

Also, $\hat{F}\left(k+i|k\right)$ is the predicted permeate output, $\hat{C}\left(k+i|k\right)$ is the predicted output of conductivity, $F^*\left(k+i|k\right)$ is the desired permeate value, $C^*\left(k+i|k\right)$ is the desired conductivity value, and finally we have the variations of the control actions $\Delta u_n(k+i-1)$ corresponding to the pressure and pH. [8]

The optimization problem is subject corresponding to pressure and pH inequality constraints through an upper bound and a lower bound for the permeate: $F_{\min}\le F(t)\le F_{\max}$, $F_{\min}$ for the minimum value of the permeate flow rate like $F_{\max}$ for maximum permeate flow rate and for conductivity: $C_{\min}\le C(t)\le C_{\max}$, $C_{\min}$ for the minimum conductivity value like $C_{\max}$ for maximum conductivity. In addition, the restrictions of the control value variables are included by establishing maximum and minimum limits. The restriction of the maximum limits $(\Delta u_{\max})$ and minimal $(\Delta u_{\min})$ of the control value for the permeate control variables are shown as follows: $\Delta u_{\min} \leq \Delta u_1 \leq \Delta u_{\max}$ and likewise Δu_2 for the second departure.

The implementation of this type of advanced control (MPC) in the PLC S7 1200 is not possible only with the manufacturer's software must resort to the help of Matlab Simulink for the design and exploitation of the code in .scl file, using the PLC coder tool and then import the TIA Portal software, with this programming blocks are generated to finally load the physical control device.

5 Reverse Osmosis Process Operating Results.

This section describes the results of the control strategies applied to the desalination process in a Hardware in the Loop simulation environment. Considering the following parameters for the MPC control: The values of the constraints are: $\Delta u_{1\min} = 0$, $\Delta u_{1\max} = 1\,000$ for pressure and $\Delta u_{2\min} = 0$, $\Delta u_{2\max} = 14$ for pH; limits of the permeate are: $F_{\min} = 0.85[gpm]$ y $F_{\max} = 2[gpm]$, the conductivity restrictions are given by $C_{\min} = 400[uS/cm]$ y $C_{\max} = 1000[uS/cm]$. On the other hand, the weights of the process variables are as follows: permeate flow weight in $\delta_1 = 11$ and conductivity weight in $\delta_2 = 11$. Finally, the weights of the control actions are: $\lambda_1 = 0.07$ y $\lambda_2 = 0.07$. Moreover, the other parameters required by the MPC control are control and horizon prediction, these are given by N_p, those that have the same samples for permeate and conductivity. For the prediction horizon, a value of $N_f = 10$, and for the control horizon, we considered a value of $N_c = 3$ every 0.1 seconds.

5.1 Virtual Reverse Osmosis Process Environment

After implementing the HIL, through the interaction of the programmable logic controller (PLC) and the virtual plant of the reverse osmosis desalination process, the following results were obtained.

Fig. 6 shows the virtual environment of the reverse osmosis process, which contains its instruments and monitoring area similar to a real process.

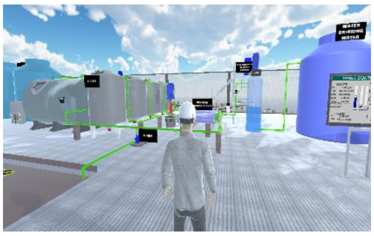

Fig. 6. Virtual environment of the reverse osmosis process.

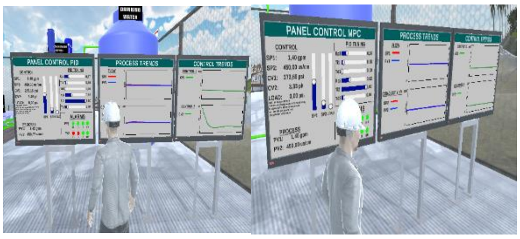

Fig. 7. Monitoring and control area

Fig.7, corresponds to the monitoring area which consists of three screens in which you can see the trends of control variables permeate flow, conductivity, as well as the parameters of the designed controllers, desired values (SP), which are part of the PID or MPC control.

Fig. 8 shows the HIL implementation, which is composed of the physical programmable logic controller (PLC) and connected by Ethernet communication to the virtualized process for controller validation.

Fig. 8. Connection between the S7-1200 PLC and the virtualized process

The PLC and the computer communicate via an Ethernet connection so the two devices must be within the same network, considering this it is necessary to check the IP address, otherwise the virtual environment will not run and will launch a message informing the connection error.

5.2 Performance of the proposed control strategies for the reverse osmosis process.

Fig. 9 a, shows the performance of the permeate flow variable against different control strategies, a PID control (green) and an MPC controller (blue). A constant set point of 1.40 gpm is used to evaluate the permeate control in the reverse osmosis process. The PID controller presents an overshoot of 3.57%, and a settling time of 62 s, from this point on there is a steady state control error of gpm. While the MPC controller presents no overshoot, and settles at 60 s, from that instant, there is a steady state error of gpm. As for the control actions, Fig. 9 b shows the manipulated variable pressure. In the PID controller, it acts from time 0 seconds to reach a steady state with a pressure of 277 psi. While the MPC control does not act quickly, this is because, in the formulation of the controller model, the effect of the conductivity process is considered.

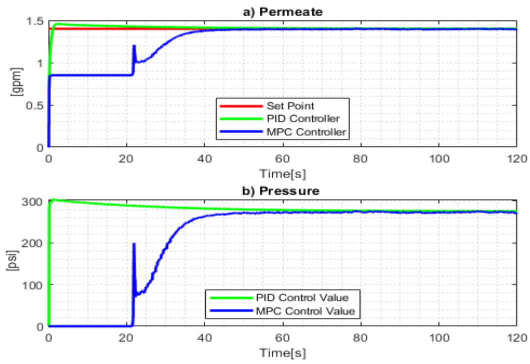

Fig. 9. a) Permeate flow response, Set Point (red), PID controller (green), MPC controller (blue), b) Manipulated variable with PID control action (green) and MPC control value (blue).

Table 1 compares the results of control parameters such as overshoot, settling time, and steady-state error of the PID and MPC controllers implemented in the reverse osmosis process corresponding to permeate.

Table 1. Performance of control algorithms to the permeate flow variable.

Parameters	PID Controller	MPC Controller
	Permeate	Permeate
Overshoot [%]	3.57	0
Settling time [s]	62	60
Steady-state error [gpm]	1×10^{-3}	6.4×10^{-5}

Fig. 10 shows the analysis of the conductivity variable of the reverse osmosis process, where: the Set Point (red), the application of a PID controller and its respective control value (green), and finally the evolution of the MPC controller and its respective control value (blue). For conductivity control, a constant set point value of 450 uS/cm was taken (see Fig. 10a). The PID controller has an overshoot of 4.23% and stabilizes at 60 s. When the controller reaches its adjustment time, the control error in the stable state is uS/cm. On the other hand, the MPC controller presents an overshoot of 6% and stabilizes at 46 s. Regarding the control action (see Fig. 10b). The MPC is faster allowing it to stabilize the system in a shorter time. As can be seen during the conductivity transient in the permeate variable there is no change, because the pressure affects the conductivity, stabilizing first the conductivity loop and then the permeate flow loop.

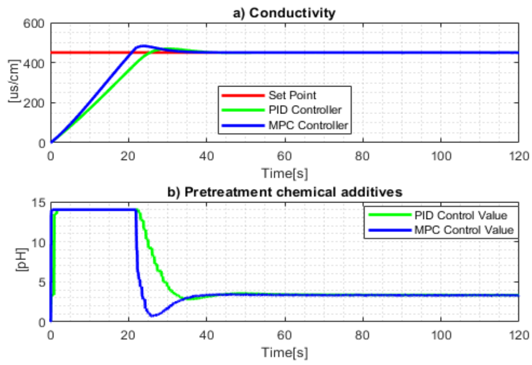

Fig. 10. a) Conductivity response, MPC controller (blue), PID controller (green), b) PID CV (green), and MPC CV (blue).

Table 2 compares the results of the control parameters such as overshoot, time adjustment, and steady-state error of the PID and MPC controllers of the conductivity variable. With this comparison it can be seen that the MPC control has better performance as it controls both control variables (pressure and pH) to control the conductivity, prioritizing this as the conductivity determines the quality of the liquid obtained at the process output. In addition, if the pressure is too high, the membrane lifetime is affected by polarization causing plugging of the membrane, which MPC has a favorable performance in controlling the pressure.

Table 2. Performance of the control algorithms to the conductivity variable.

Parameters	PID Controller	MPC Controller
	Conductivity	Conductivity
Overshoot [%]	4.23	6
Settling time [s]	60	46
Steady-state error [uS/cm]	8×10^{-3}	7×10^{-3}

For robustness analysis of controllers against disturbances, a disturbance is added by reducing the pressure to the membrane at the inlet. Fig. 12 shows the performance of the controllers against this disturbance that affects the entire system because the pressure decrease is related to the conductivity affecting the two control loops.

It has been subjected to a perturbation representing a pressure leakage to the membrane at a value of 50 psi in the second 150 in (see Fig. 11) where the performance of the PID and MPC controllers can be observed. With the MPC controller, permeate and conductivity are not affected to a great extent, while the PID controller shows larger variations when the perturbation occurs in the permeate loop. Since the MPC controller infers that the pressure control action will affect the second control loop of conductivity, it increases the pressure, making the control in this case of conductivity that determines the quality of water better, unlike the PID controller that by performing a faster action in the pressure control loop produces oscillations to the conductivity loop, in this way, it is verified that in MIMO systems the control actions affect the rest of the system, thus verifying the multivariable characteristic of the designed controller.

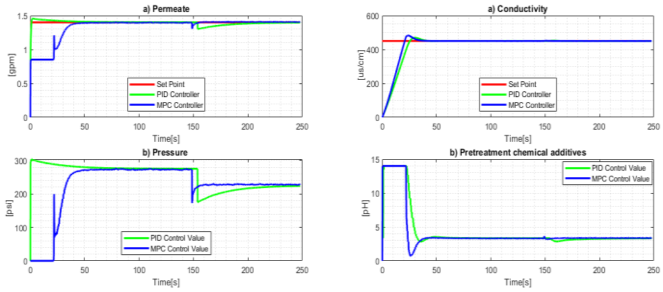

Fig. 11. Process with disturbance (pressure leakage).

6 Conclusions

The HIL technique allows the integration of PLC-programmed control algorithms operating in real-time with virtual environments of industrial processes in this case of reverse osmosis, which works in conjunction with the implemented control algorithms, reducing the cost to real processes in laboratory environments.

Input-output models based on real industrial plant measurements allow the implementation of a virtual environment similar to the industrial process with equal dynamics of the variables to be controlled within an immersive environment. This allows the application of different control algorithms, such as linear and nonlinear controllers and multivariable or more complex ones. Allowing it to be a very useful and accessible tool for learning and professional training.

The MPC controller shows a better performance in the operation of the controlled variables permeate flow and conductivity for the PID control strategy, for parameters such as overshoot, settling time, and steady-state error. Regarding the permeate flow, the PID controller presents a higher overshoot of 3.57%, while with the MPC it is 0%. The settling time of the MPC controller is 60 seconds, which is less in comparison to the PID which is 62 seconds. In both cases, the steady-state error is small and very close to zero. Regarding the conductivity, the MPC control presents an overshoot of 6% higher than the PID of 4.23%, likewise, the settling time is lower with a value of 46 seconds compared to the PID which is 60 seconds.

The MPC controller presents a better response in the control action being smoother than that produced by the PID controller, which is reflected in a better operation of the actuators as seen in the permeate loop. In addition, since the MPC controller includes the prediction model of the plant, it can be noted that in terms of the value of the controlled variables it takes into consideration the effect of pressure on conductivity.

Therefore, it stabilizes the conductivity variable first and then the permeate flow, it is important to note that the conductivity determines the quality of the output liquid and the MPC controller prioritizes this variable unlike the PID, which considers each loop as an independent process.

MPC control is robust to disturbances since it corrects the error quickly while maintaining the setpoint, while PID control, on the other hand, performs more slowly in the face of disturbances.

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