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Control performance evaluation of reverse osmosis desalination system based on model predictive control and PID controllers

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ABSTRACT

In this study, to design an efficient control system for a Reverse osmosis (RO) desalination plant, a model predictive control (MPC) was established and compared to the obtained control system based on proportional–integral–derivative (PID) controllers. In order to control two controlled variables, namely permeate flow rate and conductivity, two PID controllers' parameters were tuned based on the internal model control (IMC) rule and an MPC controller was established using the dynamic matrix control algorithm. The control performance assessment of both PID and MPC controllers were carried out using prediction error approach and their control performances were compared to that of the PID controllers which tuned by Ziegler–Nichols rule from the literature. The results showed that among the designed controllers, the PID controllers tuned by IMC method are more capable than other controllers to control the considered RO desalination plant.

Keywords: Control performance assessment; Model predictive control; Proportional–integral–derivative; Performance evaluation; Reverse osmosis

1. Introduction

Reverse osmosis (RO) membrane desalination has emerged as the leading method for water desalination due to the low cost and energy efficiency of the process. The performance of the RO plants is quite sensitive to the quality of the feed and plant operating conditions. This means that an RO plant requires a very efficient pre-treatment process and an accurate control system to maintain its operation close to the optimum conditions, which results in increased productivity and prolongs the life of the membranes due to the reduction of membrane fouling [1].

Proportional–integral–derivative controller (PID) and model predictive control (MPC) are two control strategies which are widely used to control the reverse osmosis desalination systems [2]. Control systems for reverse osmosis desalination plants based on PID and MPC controllers have been studied in the literature in particular for seawater desalination plants [3,4].

The control performance evaluation of the controllers in the sea water desalination process is one of

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the best ways to compare the performance of the controllers which are used to control the RO systems. Aiming at evaluating controller performance from route closed-loop data, control performance assessment (CPA), as a relatively young branch of research, has attached growing interest in control system monitoring and maintenance in the past few years. Based on the variance of output error, CPA techniques are used to find how current controller performance compares to the ideal control performance [5]. Recently, a few studies have been focused on using CPA techniques for assessing the control performance.

Therefore, this study contributes to use the CPA techniques to assess the control performance of the RO system controller and comparing the control performance potentials of controllers in order to select the best one in the RO desalination plant. This paper consists of three major parts. In the first part, two-input two-output (TITO) RO system was decoupled to two individual single-input single-output (SISO) systems. Two PID controllers' parameters were tuned for each control loop based on internal model control (IMC) rule. The CPA technique was used to compare the capability of the PID controller tuned by IMC and PID controller tuned by Ziegler–Nichols rule from the literature [6–8]. In the second part, a MPC controller was established and the CPA technique was used to determine the optimal tuning parameters of MPC controllers with different output weighing matrices. In the third part, the capability of MPC and PID controllers for RO desalination plant were compared together and the best one was selected among them.

2. Material and methods

2.1. RO plant description and model

Fig. 1 shows the schematic diagram of RO plant. The sea water is first pre-treated to avoid the membrane fouling in the pre-treatment system and then is passed through the membrane using a high pressure pump. Pure water permeates through the membrane and concentrated water (brine) is rejected back to the sea or sent to an energy recovery device.

Four RO system parameters which should be monitored and controlled for proper RO system performance are: feed pressure and pH as well as permeate conductivity and flux. In addition to these variables, there are others which may need to be monitored and controlled such as chlorine concentration and feed temperature [4]. In this study, the empirical model presented by Riverol and Pilipovik [9] is used to model the RO process. This model addresses two control cases: first the permeate flow rate is controlled by adjusting feed pressure and second, both the flow rate and conductivity of permeate are controlled by adjusting the feed pressure and pH [2]. As shown in Fig. 1, two valves are available to control the flow rate and conductivity of permeate, namely manipulating flow rate of chemicals at the pre-treatment unit and manipulating flow rate of the brine at the brine stream. The Laplace domain form of the linear model for considered RO plant is given by Eqs. (1)–(5) [2].

$$\begin{bmatrix} F \\ C \end{bmatrix} = \begin{bmatrix} G_{11} & G_{12} \\ G_{21} & G_{22} \end{bmatrix} \times \begin{bmatrix} P \\ \mathrm{pH} \end{bmatrix} \tag{1}$$

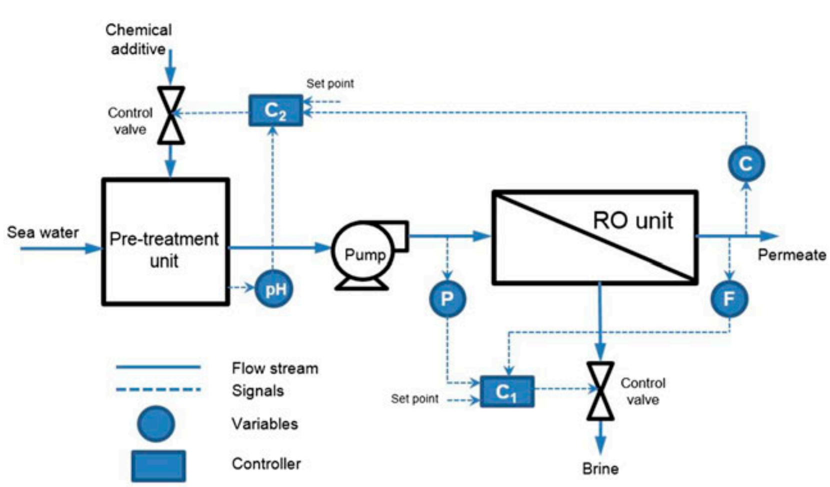

Fig. 1. Schematic of RO process.

$$G_{11} = \frac{0.002\,(0.056\,s + 1)}{0.003\,s^2 + 0.1\,s + 1} \quad (2)$$

$$G_{12} = 0 \quad (3)$$

$$G_{21} = \frac{-0.51\,(-0.35\,s + 1)}{0.213\,s^2 + 0.7\,s + 1} \quad (4)$$

$$G_{22} = \frac{-57(0.32\,s + 1)}{0.6\,s^2 + 1.8\,s + 1} \quad (5)$$

where F and C are permeate flow rate and conductivity, and P and pH are feedwater pressure and pH. The system works in a range of p = 800–1,000 kPa, F = 0.85–1.25 m^3/h, pH 6–7, and C = 400–450 µs/cm.

2.2. PID controller and tuning rule

The classic PID law is normally given by Eq. (6):

$$u\,(s) = K\left[1 + \frac{1}{s\,T_{\mathrm{i}}} + s\,T_{\mathrm{d}}\right]e\,(s) \quad (6)$$

where the controller parameters are the proportional gain K, integral time T_i, and derivative time T_d [10]. The tuning parameters of the PID controllers should be set with in-depth consideration of the process dynamic. One of the well-known empirical tuning methods is the Ziegler–Nichols empirical formula. Table 1 lists the modified Ziegler–Nichols settings for the two individual control loops calculated by Alatiqi et al. [11]. IMC is a controller design approach that uses the process model in the controller implementation [12]. In this study, IMC rule which is listed in Table 2 is used to tune the PID controllers for two individual control loops. In the considered RO process, since the G_{12} element is zero, the matrix of the process is an upper triangular which means the system has one way interaction. It means that in the RO system changing the pH of the feedwater has no effect on the permeate flow rate, while changing the feedwater pressure has effect on both the permeate flow rate and conductivity. In order to compensate the effect of the interaction, the additional controller which called decupler should be added to the system for changing the TITO system to two independent SISO control loop which is calculated by Eq. (7):

$$d_1 = \frac{G_{21}}{G_{22}} \quad (7)$$

Table 1
Modified Ziegler–Nichols settings for the two individual control loops [11]

Loop		P	PI	PID
Gp_{11}	Kc	596	536	715
	τ_I	–	0.23	0.14
	τ_d	–	–	0.03
Gp_{22}	Kc	−0.06	−0.05	−0.07
	τ_I	–	1.81	1.09
	τ_d	–	–	0.27

Table 2
IMC rules used to tune the PID controllers [12]

	K_pK	T_i	T_d	T_f
ISE optimal	$\frac{3L+2\lambda}{2L^2+4\lambda L+\lambda^2}$	$3L + 2\lambda$	$\frac{2L(L+\lambda)}{3L+2\lambda}$	$\frac{L\lambda^2}{2L^2+4\lambda L+\lambda^2}$
IAE optimal	$\frac{2}{L+\lambda}$	$2(L + \lambda)$	$\frac{L(L+2\lambda)}{2(L+\lambda)}$	–

2.3. Model predictive control (MPC)

Model predictive control has two major advantages compared to the decentralized control strategy. First, it is a multivariate control strategy which makes it more suitable for multiple inputs multiple outputs (MIMO) plant where strong interference exists among the process variables. The second selling point is that it can explicitly take constraints into account. A comprehensive review [13] is suggested for a better understanding of the evolution of MPC technique.

Consider the following quadratic cost function used in the MPC algorithm:

$$\begin{aligned} J = &\sum_{i=1}^{H_p} (\hat{y}(k+i) - r(k+i))^T \mathbf{Q} (\hat{y}(k+i) - r(k+i)) \\ &+ \sum_{i=1}^{H_u} (u(k+i) - u_0)^T \mathbf{R}_u (u(k+i) - u_0) \\ &+ \sum_{i=1}^{H_u} \Delta u(k+i)^T \mathbf{R}_{\Delta u} \Delta u(k+i) \end{aligned} \quad (8)$$

where k is the sampling instant, $\hat{y}$ is the predicted output variable, r is the set point, u is the input variable, Δu is the input rate variable, u_0 is the steady state input value, H_p the prediction horizon, H_u is the control horizon, $\mathbf{Q}$ is the output weighing matrix, $\mathbf{R}_u$ is the input weighing matrix, and $\mathbf{R}_{\Delta u}$ is the input rate weighing matrix.

The constraints can be expressed as follows:

$$\begin{aligned} &y_{\min} \le y \le y_{\max} \\ &u_{\min} \le u \le u_{\max} \\ &\Delta u_{\min} \le \Delta u \le \Delta u_{\max} \end{aligned} \tag{9}$$

2.4. Control performance assessment

CPA approaches can be classified into the several benchmarkings: MVC benchmarking, linear quadratic Gaussian benchmarking, MPC benchmarking, user specified benchmarking, historical data benchmarking, and prediction error approach (PEA) [14]. Among these methods, PEA is one of the most promising ones which describe in detail as follows:

For a multivariable process, the closed-loop output driven by a white noise can be expressed as a time series model (assuming the set point is zero):

$$Y_t = G_{\mathrm{cl}} a_t \tag{10}$$

where G_{cl} is the closed-loop time series model and a_t the white noise signal. This model can be easily obtained using the common identification procedure.

A series expansion of Eq. (10) results in the infinite order moving average model:

$$\begin{aligned} Y_t &= \sum_{k=0}^{\infty} F_k a_{(t-k)} \\ &= F_0 a_t + F_1 a_{t-1} + \cdots + F_{i-1} a_{t-(i-1)} + F_i a_{t-i} + \cdots \end{aligned} \tag{11}$$

where F_0, F_1, …, F_i are the impulse response matrices of the closed-loop time series model.

Then, the optimal ith step prediction can be obtained as:

$$Y_{t|t-i} = F_i a_{t-i} + F_{i+1} a_{t-(i+1)} + \cdots \tag{12}$$

and its prediction error:

$$e_{t|t-i} = Y_t - Y_{t|t-i} = F_0 a_t + F_1 a_{t-1} + \cdots + F_{i-1} a_{t-(i-1)} \tag{13}$$

The covariance of the prediction error can be calculated as:

$$\mathrm{cov}(e_{t|t-i}) = F_0 \Sigma_a F_0^{\mathrm{T}} + F_1 \Sigma_a F_1^{\mathrm{T}} + \cdots + F_{i-1} \Sigma_a F_{i-1}^{\mathrm{T}} \tag{14}$$

Define a scalar measure s_i as:

$$\begin{aligned} s_i &= \mathrm{tr}(\mathrm{cov}(e_{t|t-i})) \\ &= \mathrm{tr}(F_0 \Sigma_a F_0^{\mathrm{T}} + F_1 \Sigma_a F_1^{\mathrm{T}} + \cdots + F_{i-1} \Sigma_a F_{i-1}^{\mathrm{T}}) \end{aligned} \tag{15}$$

and closed-loop potential p_i as:

$$p_i = \frac{s_\infty - s_i}{s_\infty} \tag{16}$$

Finally, a CPA index expressed as p_i is obtained. This index indicates how much performance potential can be expected if process has a time delay i. Faster decay of the potential to zero indicates less possibility to improve the performance of the related controller. Therefore, controller parameters can be tuned by comparing the decay rates of p_i.

2.5. The procedure for comparing the performance of RO controllers

The frame work for comparing the performance of the RO controllers including PID controllers and MPC controller is shown in Fig. 2. First, the plant model was used, with P, and pH as manipulated variables and F, and C as controlled variables. Second, two individual control loops were defined by calculating the decouplers for TITO RO system. Third, two PID controller were tuned for two SISO control loops using IMC method. Fourth, the performance of the tuned PID controllers by IMC method was compared to the performance of the PID controllers tuned by Alatiqi [11] which used ZN method. Sixth, the MPC controller was tuned based on the tuning rules suggested by

Plant modelling

↓

Decoupling of the MIMO system to two individual SISO system

↓

Tuning of the two PID controllers internal model control (IMC)

↓

Assessing of the tuned controllers performances by IMC and ZN methods

↓

Tuning of the MPC controller parameters based on the tuning rules suggested by [] and CPA method

↓

Comparing the set point tracking performance of the PID controllers with MPC controller

Fig. 2. Frame work for comparing the controllers of the RO system.

Gurban and Andreescu [12] and the best weights for manipulated and controlled variables were defined using CPA. Seventh, the set point tracking response of the PID and MPC controllers was compared to define the best controller for RO system.

3. Results and discussion

The tuned parameters of the PID controllers obtained by IMC tuning method as well as tuned parameters obtained by ZN tuning method are shown in Table 1. CPA technique is used to compare and assess the performances of each tuned PID controller. Fig. 3 shows the comparison of the individual overall closed-loop potential between the two pairs of the PID controllers, of which one of them is tuned by IMC and other pair is tuned by ZN tuning method. As shown in Fig. 3, there are potentials for all of four tuning cases, especially when the time lag is small. For the first control loop which controls the permeate flow rate by controlling the feed pressure, the closed-loop potential of the PID controller with tune IMC1 is less than that of the PID controller with tune ZN1. It means that the PID controller with tune IMC1 can achieve better control performance than ZN1. For the second control loop which controls the permeate conductivity by controlling the feedwater pH, similar to the first control loop, the closed-loop potential of the PID controller with tune IMC2 is less than that of the ZN2. Overall, the PID controllers tuned by IMC method have lower potential to be improved compared with ZN method.

The parameters of the MPC controller were tuned using the procedure presented by Shridhar and Cooper [15]. The sampling time was chosen as 0.1 s. The prediction horizon and the control horizon were set to 20 and 1, respectively. Tuning the weighting matrixes was done as follows: first, the input weighting matrix and the input rate weighting matrix were set as zero. Since the output weighting matrix Q is important to the performance of output variables, therefore, the following six tuning scenarios with different Q matrix were considered:

$$Q_{\text{Tune1}} = \begin{bmatrix} 10 & 0 \\ 0 & 1 \end{bmatrix} \quad Q_{\text{Tune2}} = \begin{bmatrix} 1 & 0 \\ 0 & 10 \end{bmatrix} \quad Q_{\text{Tune3}} = \begin{bmatrix} 100 & 0 \\ 0 & 1 \end{bmatrix}$$
$$Q_{\text{Tune4}} = \begin{bmatrix} 1 & 0 \\ 0 & 100 \end{bmatrix} \quad Q_{\text{Tune5}} = \begin{bmatrix} 1000 & 0 \\ 0 & 1 \end{bmatrix} \quad Q_{\text{Tune6}} = \begin{bmatrix} 1 & 0 \\ 0 & 1000 \end{bmatrix} \tag{17}$$

where the first weight in the diagonal matrix is used for controlling permeate flow rate (F) and second one is used for controlling permeate conductivity (C).

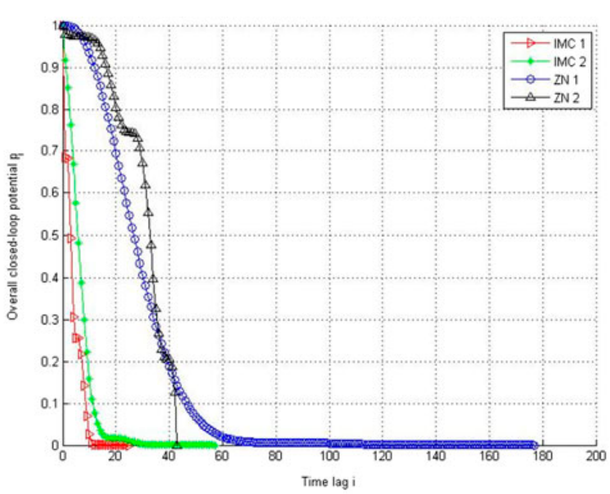

Fig. 3. Closed-loop potential from PID controllers tuned by IMC and ZN tuning methods.

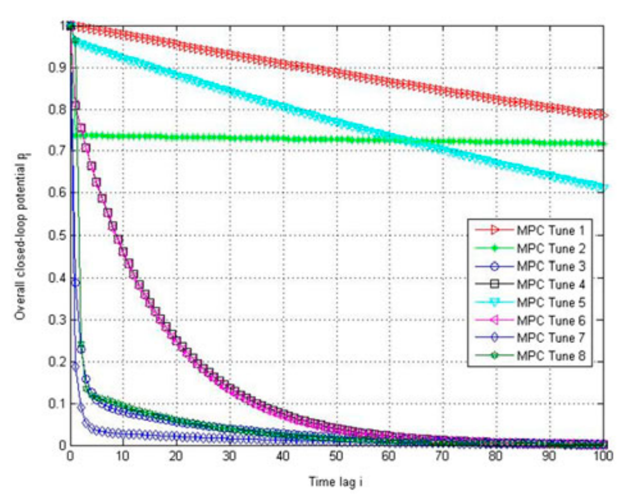

Fig. 4. Closed-loop overall potentials corresponding to the eight MPC tuning scenarios.

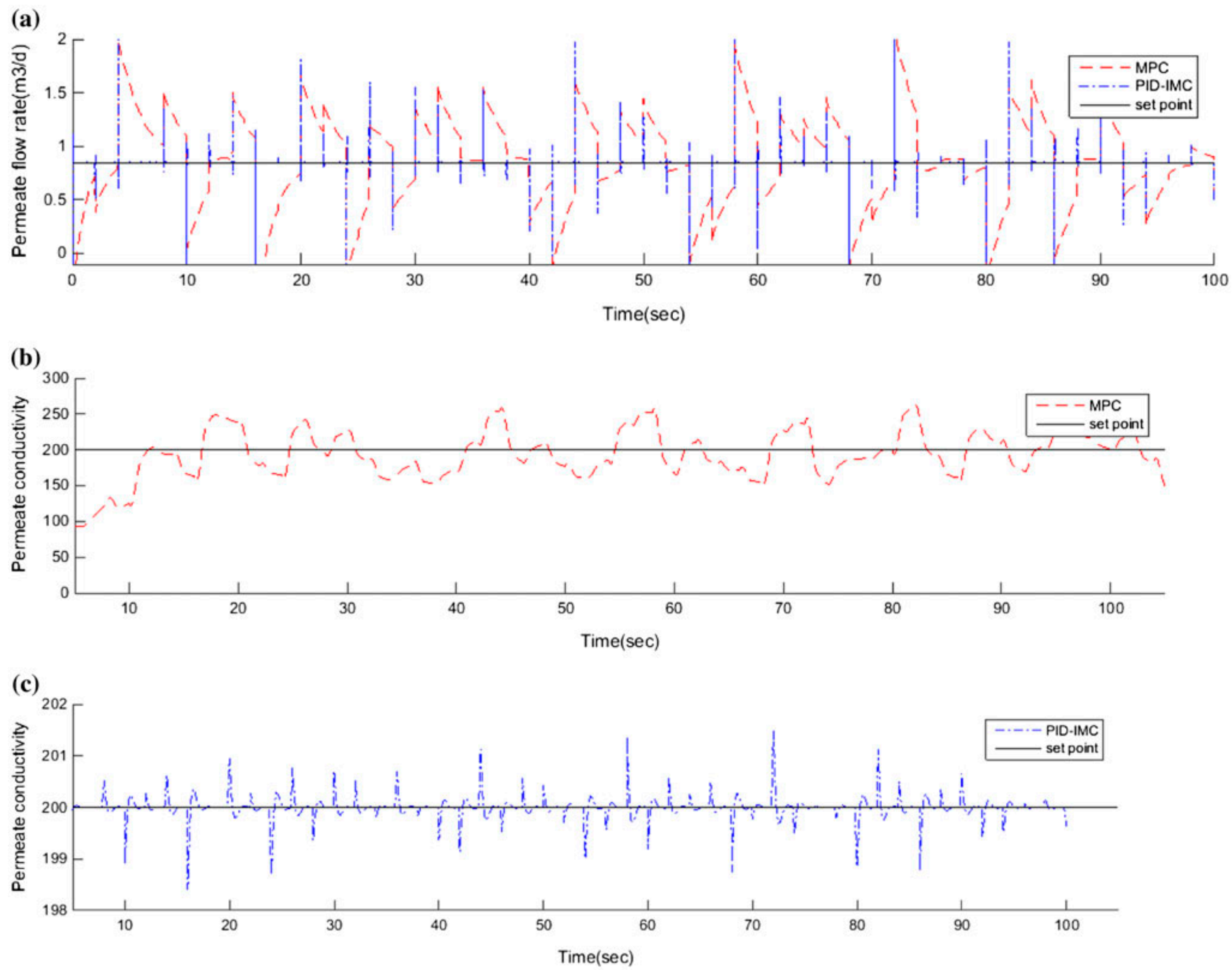

Fig. 5. Comparison of disturbance rejection performance using PID-IMC and MPC controllers for controlling to controlled variables: (a) permeate flow rate, (b) and (c) permeate conductivity.

Among the six tuning scenarios, tunes 1, 3, and 5 give more control effort to the second output variable, which means to make the permeate flow rate have higher set point tracking and disturbance rejection performance. On the other hand, tunes 2, 4, and 6 concentrate more on the permeate conductivity.

Fig. 4 shows the overall closed-loop potentials for different MPC tuning scenarios. As shown in Fig. 4 among MPC controllers tuned by scenarios 1, 3, and 5 which have the higher weight on the permeate flow rate, the MPC controller with tune 3 has less overall closed-loop positional. Also, among the MPC controllers with tunes 2, 4, and 6 which have the higher weight on the permeate conductivity, both MPC controller with tunes 4 and 6 have same closed-loop potential which is less than that of the tune 2. Overall, among the six tuning scenarios, the MPC controller with tune 3 has less positional value. Therefore, three more scenarios for tuning the MPC controller were considered which have same output weighting matrix with scenarios 3 and different input weighting matrix as follow:

$$\mathbf{R}_{u_{\text{Tune7}}} = \begin{bmatrix} 0 & 0 \\ 0 & 1 \end{bmatrix} \quad \mathbf{R}_{u_{\text{Tune8}}} = \begin{bmatrix} 1 & 0 \\ 0 & 0 \end{bmatrix} \tag{18}$$

where the first weight in the diagonal matrix is used for manipulating the feed pressure (P) and second one is used for manipulating the feedwater pH. As shown in Fig. 4, the MPC controller with tune 7 has less value of the closed-loop potential. Therefore, the MPC controller with tune 7 which has the Q_{Tune3} as the output weighing matrix and $\mathbf{R}_{u_{\text{Tune7}}}$ as the input weighting matrix is the best controller for considered RO plant.

Since among the two tuned PID controllers, the PID controller tuned by IMC method has higher performance than that of the controller tuned by ZN method, therefore, the variations of the output variables corresponding to the PID controller tuned by IMC method and MPC controller tuned by scenarios 7 were compared together with unmeasured disturbance. As shown in Fig. 5(a), the PID controller indicates faster response and the overshoot to the set point change is very small than the MPC controller. The variations of the permeate conductivity corresponding to the PID and MPC controllers are shown in Figs. 5(b) and (c), respectively. As shown in these figures, the disturbance rejection by the PID controller is very fast as the magnitude of the permeate conductivity variations is too smaller than that of the MPC controller. Therefore, the control performance of the PID control in disturbance rejection of the permeate flow rate is almost similar to the MPC controller, while the control performance of the PID control in disturbance rejection of the permeate conductivity is very higher than that of the MPC controller.

4. Conclusions

In this study, CPA technique was used to compare the PID and MPC controllers for controlling an RO desalination plant. The following conclusions can be drawn:

(1) The control performance of the PID controller tuned by internal control model (IMC) was higher than that of both PID controller tuned by Ziegler–Nichols method and MPC controller.
(2) The capability of the PID controller tuned by IMC method in disturbance rejection for the permeate flow rate is similar to the MPC controller, while its capability in disturbance rejection for the permeate conductivity is very higher than that of the MPC controller.

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List of symbols

RO	—	Reverse osmosis
PID	—	proportional–integral–derivative
CPA	—	control performance assessment
ZN	—	Ziegler–Nichols
SISO	—	single-input single-output
C	—	permeate flow conductivity
K	—	proportional gain
T_{d}	—	derivative time
$\hat{y}$	—	predicted output variable
u	—	input variable
u_0	—	steady state input value
H_u	—	control horizon
$\mathbf{R}_u$	—	input weighing matrix
MVC	—	Model View Controller
a_t	—	white noise signal
cov	—	covariance
e	—	error
MPC	—	model predictive control
IMC	—	internal model control
PEA	—	prediction error approach
TITO	—	two-input two-output
F	—	permeate flow rate
P	—	feed water pressure
T_{i}	—	integral time
k	—	sampling instant
r	—	set point
Δu	—	input rate variable
H_{p}	—	prediction horizon
$\mathbf{Q}$	—	output weighing matrix
$\mathbf{R}_{\Delta u}$	—	input rate weighing matrix
G_{cl}	—	closed-loop time-series model
F_i	—	impulse response matrix
s_i	—	scalar measure
p_i	—	closed-loop potential

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