

A modified controller design based on symbiotic organisms search optimization for desalination system

Natwar S. Rathore, V. P. Singh and Bui Duc Hong Phuc

ABSTRACT

Fresh water demand is growing drastically in many parts of the world. Desalination of seawater, brackish water, and waste water is one solution to meet the demands of fresh water. Currently, reverse osmosis (RO) desalination process is one of the best methods for the desalination process. In this study, a modified controller design is proposed for RO desalination system based on symbiotic organisms search (SOS) algorithm. A multivariable model of RO desalination plant is considered for experimentation. The RO system considered here is first decoupled using a simplified decoupling process to obtain two non-interacting loops. Then, a proportional-integral-derivative controller with second order derivative (PID-DD) scheme based on SOS algorithm is proposed for each loop to find optimal control parameters of the RO system. To design the PID-DD controller for each loop, integral of squared error (ISE) is considered as fitness function. Four other state-of-the-art optimization algorithms, namely, teacher-learner-based-optimization (TLBO), differential evolution (DE), particle swarm optimization (PSO), and artificial bee colony (ABC), algorithms are also tested for the considered system. To show competitiveness of the proposed SOS-based PID-DD controller, a comparative study based on time domain analysis is performed. Results show the SOS-based PID-DD controller is superior to other PID-DD controllers.

Key words | desalination, integral of squared error (ISE), modified controller, proportional-integral-derivative controller with second order derivative (PID-DD), reverse osmosis (RO), symbiotic organisms search (SOS) optimization

Natwar S. Rathore (corresponding author)
V. P. Singh
Department of Electrical Engineering,
National Institute of Technology,
Raipur,
India
E-mail: natwarsmertia@gmail.com

Bui Duc Hong Phuc
School of Intelligent Mechatronics Engineering,
Sejong University,
Seoul,
Republic of Korea

INTRODUCTION

Desalination is a method by which seawater and brackish water is filtered out in the form of fresh water by using chemical and physical processes so that the unusable water is made available for industrial, irrigation, and drinking purposes (Sobana & Panda 2011). In the last few years, significant developments in the area of desalination technologies have been seen all over the world. At present, many desalination techniques such as multistage-flash distillation (MSF), multiple-effect distillation (MED), evaporation, vapor-compression (VC), and membrane processes are used for water treatment. Among all the desalination methods, the reverse osmosis (RO) water treatment

method is accepted worldwide due to its simplicity and high performance with minimal cost requirements (Sobana & Panda 2014).

The RO desalination process, in spite of being simple, is easy to implement and versatile in nature, and thus can be used for treatment of water; but still the technology suffers from the problems of membrane fouling and concentration polarization (Madaeni *et al.* 2015). However, these problems can be solved with advance technology in terms of process and control optimization. Traditionally, a combination of proportional-integral-derivative (PID) controller is incorporated to fulfill the control objectives in many applications.

Alatiqi *et al.* (1989) first proposed traditional PID controllers in RO desalination plants. Furthermore, Robertson *et al.* (1996) used a modified Ziegler–Nichols (MZN) method for the tuning of PID controller parameters. Classically, the PID controllers are tuned with conventional techniques such as Ziegler–Nichols, MZN, trial and error method, Cohen and Coon (Bennett 2001), etc. Simple PID controllers with conventional tuning methods do not provide satisfactory results with plant and model uncertainties. A model predictive control (MPC) approach is presented in Abbas (2006) to overcome the limitations of PID controllers in RO desalination units. With the evolution of various optimization techniques, conventional methods of PID controller tuning are being replaced by optimization-based techniques (Åström & Hägglund 2006; Rathore *et al.* 2015a, 2015b; Gupta *et al.* 2016).

A literature survey shows that researchers have used many intelligent optimization techniques for the RO desalination problem. Zilouchian & Jafar (2001) and Kim *et al.* (2008) presented a genetic algorithm (GA)-based controller design for RO desalination plants. In Gambier (2011), a multi-objective optimization-based controller was designed for RO desalination systems. Although the algorithm is found to be superior to conventional methods, it still suffers from proper tuning of algorithm-specific parameters. Fuzzy logic and neural networks have been applied to investigate the RO desalination problem (Madaeni *et al.* 2015). Phuc *et al.* (2016) suggested a modified PID controller based on H_∞ loop shaping method for desalination plants. However, the problem associated with these controllers is that they increase the complexity, mathematical complications, and computational efforts in the controllers. Therefore, in these techniques, the researchers/engineers need expert knowledge of the complex procedure and its applicability for practical use in RO desalination plants. This makes them less popular among researchers/engineers. Hence, the design procedure for the aforementioned controller needs further investigation (Jiang *et al.* 2016). Moreover, there are no limitations associated with classical PID controllers, which are simple, reliable, and affordable to use (Gambier *et al.* 2009). Therefore, optimization-based controller techniques have proven themselves in terms of better performance, simplicity, and less computation efforts required for the optimal tuning of controller parameters.

Rathore & Singh (2018) proposed a PID controller using teacher-learner-based optimization (TLBO) for RO desalination. The proposed method shows its superiority over other state-of-the-art techniques available in the literature. Recently, Sahib (2015) presented a new controller scheme, which is a combination of PID controller with second order derivative controller (DD). This combination is newly adopted and found to be efficient in a few research problems such as automatic voltage regulator (AVR) (Sahib 2015), automatic generation control (AGC) (Raju *et al.* 2016), etc. However, this control technique is not implemented in RO desalination systems.

In the current work, a new optimization algorithm, i.e., symbiotic organism search (SOS), proposed by Cheng & Prayogo (2014), is applied to design a PID-DD controller for RO desalination plants. The tuning of parameters for PID-DD controllers is achieved by minimizing the integral of square error (ISE) criterion. The RO model proposed by Riverol & Pilipovik (2005) is considered for experimental testing. In this procedure, a simplified decoupling method is first used to transform the multivariable RO model to a single-input single-output (SISO) model. Then, the proposed SOS-based controllers are examined for permeate flux and conductivity variables, respectively. Comparative studies of the proposed controllers with TLBO, DE, PSO, and ABC algorithm-based PID-DD controllers are presented in order to prove its supremacy over others.

The remainder of the paper is organized as follows. The section below introduces the RO seawater desalination process and its model structure. This is followed by a section that gives the modified controller design approach used in this work. Then the basics of the SOS algorithm applied to a RO desalination plant are discussed. Simulation results and comparison follow and the final section concludes the paper and discusses future avenues of research.

REVERSE OSMOSIS SEAWATER DESALINATION PROCESS

A generalized layout for a RO desalination system is shown in Figure 1. In this model, the RO system is characterized by four main segments, i.e., pre-treatment, high-pressure pump, membrane module, and post-treatment (Gambier *et al.*

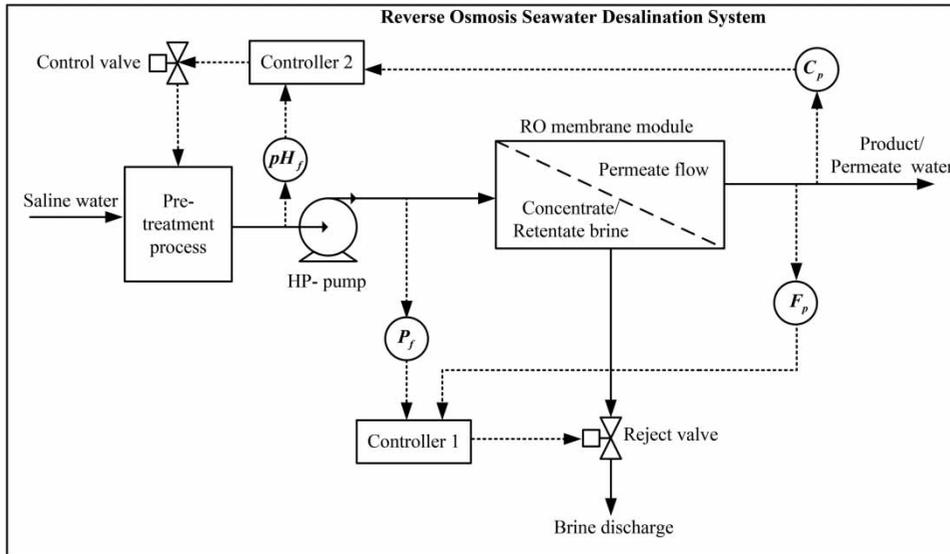


Figure 1 | Generalized layout of RO seawater desalination system.

2009). In the first segment, i.e., pre-treatment, saline water obtained from the sea or any other source is filtered through a chemical and physical process to remove major impurities present in the water. This process is very important in RO desalination plants in order to enhance the life cycle of the RO membrane. Also, it reduces scaling and fouling. In the next segment, a high-pressure pump is provided to raise the pressure of incoming water from the pre-treatment process. In the subsequent segment, the pressurized water is fed to a membrane assembly module. The membrane assembly module should be strong enough to withstand pressurized feed water. Therefore, the RO membrane assembly module is made up of a composite polyamide-type membrane, which is widely used in many RO desalination plants. After passing through membrane assembly, fresh water accumulates in a storage tank and brine water is discarded by the membrane accumulates at the discharge channel. The fresh water obtained from this process is post-treated in the last segment by adding some inhibitors and adjusting the pH value to the appropriate level (Rathore & Singh 2018).

Figure 1 contains all four segments, manipulated variables, and control variables. Manipulated variables are P_f (pressure) and pH_f (pH value) at feed stream, respectively, and control variables are F_p (flux) and C_p (conductivity) at permeate stream, respectively.

Modeling of RO seawater desalination system

The RO segments are generally modeled according to mass transfer equations. Finite-difference methods (FDMs) are used to approximate these transfer equations into algebraic equations. The first algebraic model of the RO system was proposed by Alatiqi *et al.* (1989) at Doha laboratory. Thereafter, different models of RO system have been developed by many researchers. In the present work, a multi-input multi-output (MIMO) dynamic model proposed by Riverol & Pilipovik (2005) is used for the experiment. There are two control-loops, one is for pressure at the feed stream to control flux and conductivity at the permeate stream and the second is for pH at the feed stream to regulate conductivity at the permeate stream in this model. The algebraic transfer function equations are identified based on this model and can be represented as follows:

$$\begin{bmatrix} F_p(s) \\ C_p(s) \end{bmatrix} = \underbrace{\begin{bmatrix} P_{11}(s) & P_{12}(s) \\ P_{21}(s) & P_{22}(s) \end{bmatrix}}_{G(s)} \times \begin{bmatrix} P_f(s) \\ pH_f(s) \end{bmatrix} \quad (1)$$

where F_p (m^2/d) is flux rate and C_p ($\mu\text{s}/\text{cm}$) is conductivity at the permeate stream, while P_f (kPa), and pH_f are the pressure and pH values at the feed stream. The transfer function values for $P_{11}(s)$, $P_{12}(s)$, $P_{21}(s)$, and $P_{22}(s)$ are

represented as follows:

$$P_{11}(s) = \frac{0.0045(0.104s + 1)}{0.012s^2 + s + 1} \tag{2}$$

$$P_{12}(s) = 0 \tag{3}$$

$$P_{21}(s) = \frac{-0.12s + 0.22}{0.1s^2 + 0.3s + 1} \tag{4}$$

$$P_{22}(s) = \frac{10(-3s + 1)}{s^2 + 5s + 1} \tag{5}$$

The transfer function Equations (2)–(5) in standardized form can be represented as:

$$P(s) = \frac{K_{pr}(\tau_\alpha s + 1)}{\tau^2 s^2 + 2\zeta\tau s + 1} \tag{6}$$

where K_{pr} , τ_α , τ , and ζ represent process gain, numerator zero, time constant, and damping ratio, respectively.

The operating range for the linear model parameters of RO system is as listed in Table 1.

Decoupling in RO desalination system

As it is clear from Equation (1) that the RO seawater desalination system is a MIMO process, therefore, to handle the problem of interaction in between two loops, it is required to design a perfect decoupler (Luyben 1970). Decoupler formation is shown in Figure 2. P_{d12} and P_{d21} are feed-forward transfer functions, calculated using a simplified decoupling process, which is represented by Equations (7) and (8), respectively:

$$P_{d12}(s) = \frac{P_{21}(s)}{P_{22}(s)} \tag{7}$$

$$P_{d21}(s) = \frac{P_{12}(s)}{P_{11}(s)} \tag{8}$$

Table 1 | Operating range of system parameters

System parameters	Range
Feed pressure (P_f)	800–1,000 (kPa)
Feed pH (pH_f)	6–7.2
Permeate flux-rate (F_p)	33,000–15,400 (m ² /d)
Permeate conductivity (C_p)	400–500 (μs/cm)

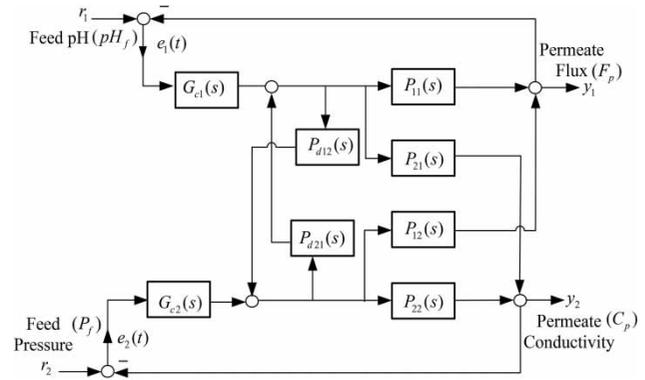


Figure 2 | Decoupled system of reverse osmosis desalination system.

PROPOSED MODIFIED CONTROLLER SCHEME

The proposed modified controller consists of a PID controller with a DD controller. The second order derivative or double derivative controller provides a better response than PID control structures (Sahib 2015). The control structure of PID-DD is illustrated in Figure 3.

The continuous time expression for the PID-DD controller in ideal form is provided by:

$$u(t) = K_p e(t) + K_i \int_0^t e(t) dt + K_d \frac{d}{dt} e(t) + K_{dd} \frac{d^2}{dt^2} e(t) \tag{9}$$

where K_p is proportional gain, K_i is integral gain, K_d is differential gain, and K_{dd} is double differential gain, $u(t)$ and $e(t)$ represent controller response and error function, respectively. The corresponding transfer function in Laplace domain is represented as:

$$u(s) = K_p + \frac{K_i}{s} + K_d s + K_{dd} s^2 \tag{10}$$

The four parameters of the modified controller are tuned with different optimization algorithms for minimizing the ISE criterion.

The ISE is provided by Equation (11):

$$J_{ISE} = \int_0^\infty e^2(t) dt \tag{11}$$

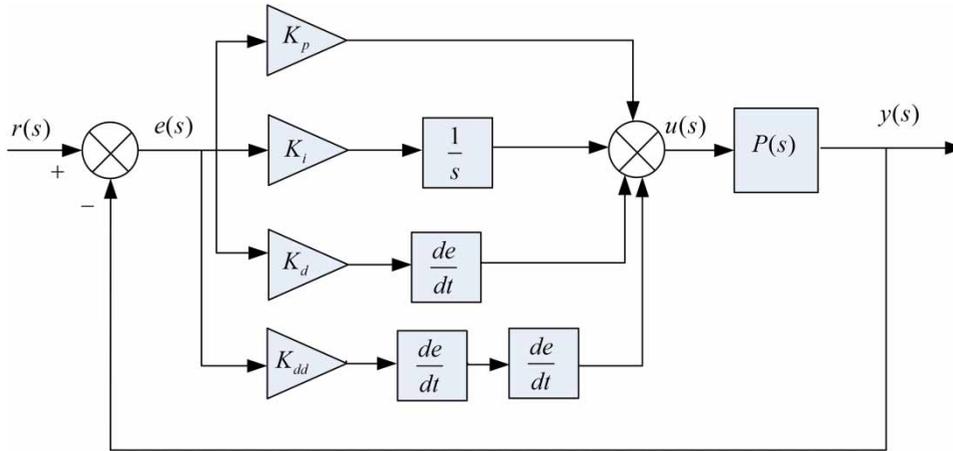


Figure 3 | PID with second order derivative controller (PID-DD) structure.

The ISE formulated in Equation (11) is minimized subject to the following constraints:

$$\left. \begin{aligned} K_p^{\min} &\leq K_p \leq K_p^{\max} \\ K_i^{\min} &\leq K_i \leq K_i^{\max} \\ K_d^{\min} &\leq K_d \leq K_d^{\max} \\ K_{dd}^{\min} &\leq K_{dd} \leq K_{dd}^{\max} \end{aligned} \right\} \quad (12)$$

The ISE is evaluated by alpha-beta table formation, represented as:

$$J_{ISE} = \frac{1}{2} \sum_{i=1}^p \frac{\beta_i^2}{\alpha_i} \quad (13)$$

where α_i and β_i are alpha and beta coefficients, respectively, which are obtained from alpha and beta tables (Åström 1970), and p is the order of error function $e(s)$.

SYMBIOTIC ORGANISMS SEARCH OPTIMIZATION

SOS optimization is a newly developed metaheuristics algorithm based on the natural phenomenon of organisms (Cheng & Prayogo 2014). The SOS algorithm shows the symbiotic relationship within paired organisms present in the ecosystem. Similar to other organisms like honeybee swarms, particle swarm optimization, and genetic algorithms, the SOS optimization algorithm uses the bunch of

population and it searches the global best solution for the given problem within the search space. In this algorithm, there are three phases based on the relationships of real-world organisms. The three phases are mutualism, commensalism, and parasitism phases.

Further details of these three phases are given as follows.

Mutualism phase

As the name suggests interaction in this phase will benefit both the organisms in the ecosystem. Suppose, S_i is an organism which is the i^{th} member of the ecosystem and S_j is another organism selected randomly from the ecosystem (where $i \neq j$). Both organisms (i.e., S_i and S_j) interact mutually with each other for survival in the ecosystem. The new solutions obtained from this phase are modeled as follows:

$$S_i^{new} = S_i + rand(0, 1) * (S^{best} - MV * B_{f_1}) \quad (14)$$

$$S_j^{new} = S_j + rand(0, 1) * (S^{best} - MV * B_{f_2}) \quad (15)$$

where MV is mutual factor which is calculated as $MV = \frac{S_i + S_j}{2}$, B_{f_1} and B_{f_2} are the beneficial factors for organisms S_i and S_j , respectively. The beneficial factors (i.e., B_{f_1} and B_{f_2}) are considered as either 1 or 2, decided randomly with equal probability, and S^{best} represents the highest degree of adaptation among both organisms.

Commensalism phase

In this phase, one organism gets benefits from the other organism but the other remains unaffected. This relationship is called the commensalism phenomenon. The modified solution is updated in this phase according to the equation shown below:

$$S_i^{new} = S_i + rand(-1, 1) * (S^{best} - S_j) \tag{16}$$

where S_i and S_j are two organisms of the ecosystem, S^{best} is the best organism in the current population, and S_i^{new} is updated value of S_i .

Parasitism phase

In parasitism, only one organism benefits, but the other organism is harmed by the first organism. In this way, plasmodium parasites pass into the human body with the help of Anopheles mosquitoes, where they get food and increase their population and, in return, humans suffer from malaria and may die.

In the SOS algorithm, a parasite vector is created by duplicating S_i organisms in the search space. Further,

Table 2 | PID-DD controller parameters obtained from different algorithms for case study 1

Algorithms	PID-DD parameter values			
	K_{p1}	K_{i1}	K_{d1}	K_{dd1}
SOS-PID-DD	800.4356	1,248.7717	86.9817	20.8975
TLBO-PID-DD	468.0110	1,475.5126	149.9817	18.0496
DE-PID-DD	514.8157	1,468.0129	148.9012	39.6841
PSO-PID-DD	428.1203	1,388.3628	264.3257	11.2334
ABC-PID-DD	413.9842	1,365.1558	246.2006	26.9244

Table 3 | Performance for permeate flux-rate with PID-DD controller for case study 1

Parameters	Controllers				
	SOS-PID-DD	TLBO-PID-DD	DE-PID-DD	PSO-PID-DD	ABC-PID-DD
Performance index (ISE)	1.8762×10^{-4}	2.83469	1.86968	2.6128	2.9022
Rise time	0.39481	0.43864	0.6801	0.5340	0.4925
Settling time	2.5084	3.8895	18.7737	9.7542	11.1940
Overshoot (%)	3.8913	12.5346	20.1320	22.0740	26.7780
Peak	1.0389	1.1253	1.2013	1.2207	1.2677

organisms S_i are modified randomly using a random number to obtain the parasite vector. Organisms S_j are treated as host in the ecosystem for the parasite vector. This parasite vector tries to replace S_j . If the fitness of the parasite vector is better than that of S_j , then the parasite vector will replace S_j .

The steps for the SOS algorithm are given as follows:

Step 1: Generate initial population in the ecosystem randomly.

Step 2: Determine the fitness value and find their S^{best} value for each organism.

Step 3: Select the S_j randomly such that $S_j \neq S_i$ (*Mutualism phase*)

Step 4: Calculate mutual vector $MV = (S_i + S_j)/2$ and benefit factor (B_f) either 1 or 2.

Step 5: Modify the solution according to Equations (14) and (15).

if $S_{i,j}^{new}$ is better than $S_{i,j}^{best}$ then

$$S_{i,j}^{new} \leftarrow S_{i,j}^{best}$$

end if

(*Commensalism phase*)

Step 6: Repeat step 3 and modify the solution according to Equation (16).

(*Parasitism phase*)

Step 7: Repeat step 3 and create parasite vector from S_i . Calculate the fitness value

if Parasite vector better than S_j then

$$S_j \leftarrow \text{Parasite vector}$$

end if

Step 7: Repeat step 2 and proceed for next iteration.

Step 8: Stop if termination criterion is met.

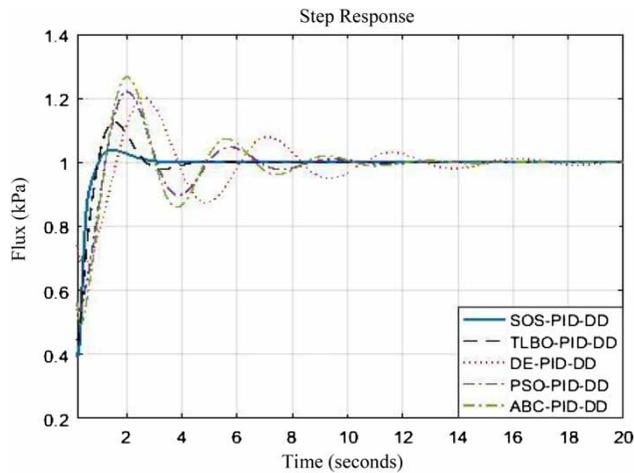


Figure 4 | Step response plot for case study 1.

Table 4 | PID-DD controller parameters obtained from different algorithms for case study 2

Algorithms	PID-DD parameter values			
	K_{p2}	K_{i2}	K_{d2}	K_{dd2}
SOS-PID-DD	4.8001	20.0607	2.0909	0.0250
TLBO-PID-DD	2.2136	18.0293	2.9087	0.0341
DE-PID-DD	1.6001	16.0607	2.02679	0.0922
PSO-PID-DD	0.77192	8.0531	2.0853	0.0862
ABC-PID-DD	0.976	6.1057	2.0473	0.0162

RESULTS AND COMPARISONS

Two case studies are considered in this work to examine the performance of the modified PID controller with different optimizing techniques presented in the literature. The

objective function designed in Equation (13) is tested for permeate flux and conductivity parameters, respectively.

Case study 1

In the first case, the performance of the PID-DD controller with SOS, TLBO, DE, PSO, and ABC optimization algorithms is tested. The PID-DD controller parameters obtained from different algorithms are presented in Table 2 and performance indices are given in Table 3. It is found that the minimum performance index is found with the SOS-based PID-DD (SOS-PID-DD) controller. Time response analysis for flux is plotted in Figure 4 and their values are tabulated in Table 3.

Case study 2

In the second case, to establish the capability of the proposed SOS-PID-DD controller, other controllers based on TLBO, DE, PSO, and ABC optimization algorithms are also designed for loop 2. The PID-DD controller parameter values are presented in Table 4 and performance indices are tabulated in Table 5. It is obvious from simulation results that performance index is minimum for the SOS-PID-DD controller. Time response analysis for conductivity with the PID-DD controller using different algorithms is shown in Figure 5 and their time response specifications are also tabulated in Table 5 for comparison.

Figures 4 and 5 and Tables 3 and 5 clearly establish that the RO system performance is appreciably enhanced with the SOS tuned PID-DD controller.

Table 5 | Performance for permeate conductivity with PID-DD controller for case study 2

Parameters	Controllers				
	SOS-PID-DD	TLBO-PID-DD	DE-PID-DD	PSO-PID-DD	ABC-PID-DD
Performance index (ISE)	0.0322	0.1610	0.4050	0.4370	0.5029
Rise time	0.9807	0.9804	0.9723	0.8552	0.9636
Settling time	3.9597	10.7761	15.1472	28.1165	15.6693
Overshoot (%)	0.6513	1.3364	2.2324	3.1152	2.5406
Peak	1.0065	1.0133	1.0223	1.0312	1.0254

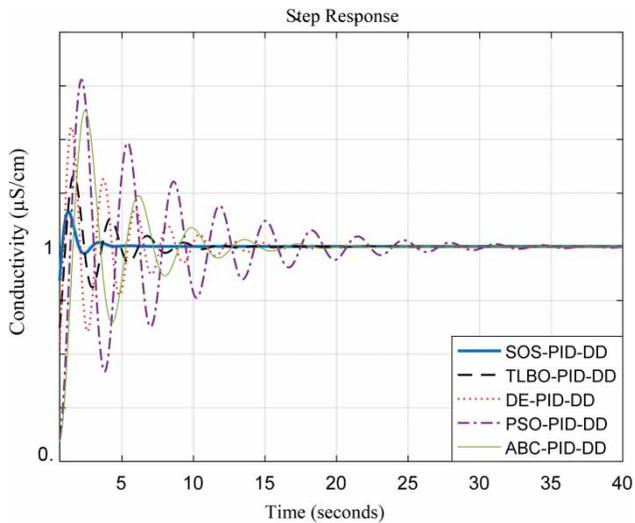


Figure 5 | Step response plot for case study 2.

CONCLUSION

In this work, a new optimization approach, i.e., SOS is tested for PID with a second order derivative (DD) controller to examine the performance of permeate flux and conductivity parameters of an RO system. The effect of the SOS algorithm with the PID-DD controller is found to be superior to other methods of optimization in the literature. Hence, it can be concluded that the proposed method is quite satisfactory and can be successfully implemented for RO desalination plants. Future work includes the design and tuning of a modified PID-DD controller for other models proposed for RO desalination plants. Additionally, this work can be extended to design a robust modified PID-DD controller for RO desalination plants.

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