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Design of optimal PID controller for the reverse osmosis using teacher-learner-based-optimization

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Abstract. In this contribution, the control of multivariable reverse osmosis (RO) desalination plant using proportional-integral-derivative (PID) controllers is presented. First, feed-forward compensators are designed using simplified decoupling method and then the PID controllers are tuned for flux (flow-rate) and conductivity (salinity). The tuning of PID controllers is accomplished by minimization of the integral of squared error (ISE). The ISEs are minimized using a recently proposed algorithm named as teacher-learner-based-optimization (TLBO). TLBO algorithm is used due to being simple and being free from algorithm-specific parameters. A comparative analysis is carried out to prove the supremacy of TLBO algorithm over other state-of-art algorithms like particle swarm optimization (PSO), artificial bee colony (ABC) and differential evolution (DE). The simulation results and comparisons show that the purposed method performs better in terms of performance and can successfully be applied for tuning of PID controllers for RO desalination plants.

Keywords: desalination; integral of squared error (ISE), PID controller; reverse osmosis (RO); simplified decoupling; teacher-learner-based-optimization (TLBO)

1. Introduction

The fresh water demand is increasing rapidly all over the world due to rise in population, irrigation area and industrial need all over the world. The lack of available natural water resources instigated to look for new alternatives around the world to meet the fresh water demand. The desalination of sea/brackish water is one of the alternatives to meet these requirements. Multi-stage flash (MSF) desalination and reverse osmosis (RO) processes are two mostly used techniques for desalination of sea/brackish water (Alatiqi *et al.* 1989). However, RO process is preferred over MSF on a wide scale due to less amount of energy consumption. At present, RO process is becoming most well-known and popular filtration process producing fresh water at low cost and low energy consumption (Malwatkar *et al.* 2009, Bartman *et al.* 2010, Karuppiah *et al.* 2012). High product quality and reliability are its added advantages.

Many researchers in their studies suggested different model structures for RO desalination. In (Alatiqi *et al.* 1989), a multi-loop control design structure is presented for RO plants, where one pressure control variable and two pH control variables are used. In (Robertson *et al.* 1996), a model-based control system is described for RO plants, where two output variables i.e., permeate flow rate and conductivity were considered. However, this approach is not found successful for large-scale RO plants. Article (Chaaben, Andoulsi *et al.* 2011) developed a MIMO model approach based on empirical transfer function matrix for a small photovoltaic RO plant. The practical implementation of these methods is difficult due to parametric uncertainties, large computational time involved and selection of manipulated and control variables.

In RO desalination plants, membranes are very sensitive to formation of concentration layer due to which high concentrate volumes are deposited on the membrane side. As a result, membrane fouling occurs which degrades the membrane performance resulting in its frequent replacement (Bartels *et al.* 2005). This, in turn, changes the system parameters rapidly and increases the production cost of RO water.

In recent, many works have been reported in the optimum tuning of controller parameters with state-of-art optimization algorithms. Articles (Kim *et al.* 2008, Kim *et al.* 2009) are devoted to the applications of immune genetic algorithm (IGA) and real-coded genetic algorithm (RCGA) for tuning of PID controller for the RO system. The authors presented a comparison of these algorithms with classical Ziegler-Nichols (ZN) tuning method. In (Gambier *et al.* 2009), the improvement of controller parameters is proposed using game theory. A PSO based PID controller tuning is proposed by Rathore *et al.*, where a comparative study with ZN tuning method is given for RO system (Rathore *et al.* 2013). The main limitations of applying these approaches lie in the proper tuning of algorithm-specific parameters, which is the utmost requirement for the effectiveness of these algorithms. However, tuning of the controller with algorithm-specific parameters increases sluggishness and computational time in the plants.

In this work, simplified decoupling based PID

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controllers are presented for the unit model of RO system. The tuning of these PID controller-parameters are accomplished with minimization of the integral of squared error (ISE) performance criterion. The ISEs are minimized using a new optimizing algorithm i.e., TLBO, which doesn't need any algorithm-specific parameters and is one of the popular technique used in mechanical designs, benchmark functions and numerical solutions to many linear and non-linear optimization problems (Rao and Patel 2013, Basu 2014, Baykasoğlu *et al.* 2014). The experimental results show the comparisons of TLBO based PID controllers with the controllers designed using PSO, ABC and DE algorithms.

The remainder of this paper is organized as follows. The reverse osmosis plant is introduced in section 2. The details of control strategy using simplified decoupling are discussed in section 3. Section 4 discusses the proposed method of tuning, experimental settings, and performance metric. Section 5 describes the basics of TLBO algorithm. Section 6 gives the experimental results followed by discussion. Finally, the concluding remarks are presented in Section 7.

2. The basics of reverse osmosis plant

The reverse osmosis desalination plant comprises four main stages: pre-treatment, high-pressure pump, RO membrane assembly and post-treatment (Gambier *et al.* 2009). The saline water is first treated in the pre-treatment stage to avoid scaling problem in RO plants, thus, preventing RO membranes from degradation.

In this stage, pH value of saline water is adjusted by adding some inhibitors. Then, it is passed through sand filter which removes suspended impurities like solid particles, microorganisms, etc. of the range 0.005-0.050 Kg/m3 (5-50 mg/l). Further, activated cartridge filters trap organic chemicals and chlorine of the range 5-10 µm. The high-pressure pump supplies the pressure needed to push feed water through the membrane assembly. Typically, the range of pressure for brackish water is around 1.6-2.6 MPa (225-325 psi) and for sea-water, it is around 6-8 MPa (800-1180 psi). Because of this pressure, water gets separated out from the saline water after passing through RO membrane assembly retaining concentrate (brine) at brine discharge.

Membrane assemblies have two or more semi-permeable membranes consisting of thin-film composite polyamide type membrane. In post-treatment stage, product water is stabilized with adjustment in pH level in the range of 6 to 8 and is prepared for distribution. The generalized schematic block diagram of the RO system is shown in Fig. 1.

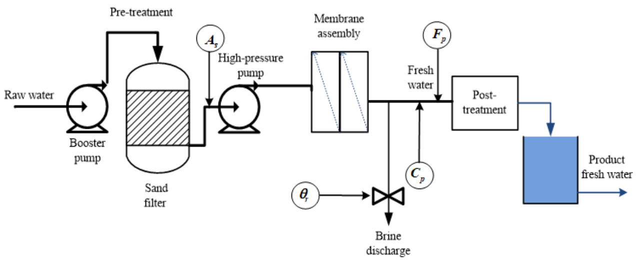

Fig. 1 A schematic block diagram of RO system

Fig. 1 demonstrates all four stages of RO system along with variables of interest: flux-rate (F_p) and conductivity (C_p) of permeate as controlled variables and, angular speed of high-pressure pump (A_s) and reject valve aperture (θ_r) as manipulated variables.

3. Design of control system for reverse osmosis module

The prime task in control system design of a RO membrane is to maintain a certain flux-rate at permeate side with lowest possible value of operating pressure at the inlet side as it results in reduction of the operation costs i.e., electric power consumed by the high-pressure pump and most important it extends the life of membrane assembly used in the plant. Hence, a suitable controller design will enhance the performance of RO system.

In this work, the multivariable model given by (Chaaben *et al.* 2011) is considered for the experimental purpose. The relation between output variables and input variables of RO module are represented as follows

$$Y = \begin{bmatrix} F_p \\ C_p \end{bmatrix} \quad \text{and} \quad U = \begin{bmatrix} A_s \\ \theta_r \end{bmatrix} \tag{1}$$

where F_p is flux (flow) rate and C_p is conductivity and these are considered as the fundamental control variables at the permeate side and are responsible for maintaining product water quantity and quality. A_s is angular speed of the pump and θ_r is reject valve aperture. These two parameters are treated as manipulated variables at the feed side. The MIMO RO unit model transfer function can be represented as follows

$$\left[G_p(s)\right] = \begin{bmatrix} G_{p11}(s) & G_{p12}(s) \\ G_{p21}(s) & G_{p22}(s) \end{bmatrix} \tag{2}$$

where $G_{p11}(s)$, $G_{p12}(s)$, $G_{p21}(s)$ and $G_{p22}(s)$ are first and second order elementary transfer function models and are represented as follows

$$G_{p11}(s) = \frac{F_p}{A_s} = \frac{k_{11}}{(1+\tau_{11}s)} \tag{3}$$

$$G_{p12}(s) = \frac{F_p}{\theta_r} = \frac{-\omega_1^2}{(s^2 + 2\xi_1\omega_1 s + \omega_1^2)} \tag{4}$$

$$G_{p21}(s) = \frac{C_p}{A_s} = \frac{-\omega_2^2}{(s^2 + 2\xi_2\omega_2 s + \omega_2^2)} \tag{5}$$

$$G_{p22}(s) = \frac{C_p}{\theta_r} = \frac{k_{22}}{(1+\tau_{22}s)} \tag{6}$$

where nominal values of the parameters are obtained using system identification. The model parameters values are given in Appendix A (Chaaben *et al.* 2011).

3.1 Decoupling of RO model system

The RO plant model is basically the MIMO system having the combination of more than one input and output variables. It means one input variable affects more than one output variables. To avoid such type of problem of interaction, decoupling method is used in many controller designs (Riverol and Pilipovik 2005, Kim *et al.* 2008, Park *et al.* 2009). A design of decoupling control system for RO system is shown in Fig. 2.

Decoupling at the input of a two input two output (TITO) process $G_p(s)$ requires the design of a transfer matrix $G_{ff}(s)$ such that $G_p(s)G_{ff}(s)$ is a diagonal transfer matrix $T(s)$ (Gagnon *et al.* 1998). Hence, matrices, $G_{ff}(s)$, $G_p(s)$, and $T(s)$, given in Eqs., (2), (7) and (8), respectively.

$$G_{ff}(s) = \begin{bmatrix} G_{ff11}(s) & G_{ff12}(s) \\ G_{ff21}(s) & G_{ff22}(s) \end{bmatrix} \tag{7}$$

and

$$T(s) = \begin{bmatrix} T_{11}(s) & 0 \\ 0 & T_{22}(s) \end{bmatrix} \tag{8}$$

should satisfy

$$G_p(s)G_{ff}(s) = T(s) \tag{9}$$

In this work, decoupling control design method proposed by (Luyben 1970), known as simplified decoupling, has been used. In this technique, the decoupler $G_{ff}(s)$ is given by

$$G_{ff}(s) = \begin{bmatrix} 1 & G_{ff12}(s) \\ G_{ff21}(s) & 1 \end{bmatrix} \tag{10}$$

where

$$G_{ff21}(s) = -\frac{G_{p21}(s)}{G_{p22}(s)}, \quad G_{ff12}(s) = -\frac{G_{p12}(s)}{G_{p11}(s)}.$$

The resulting transfer matrix $T(s)$ can be formed as

$$T(s) = \begin{bmatrix} G_{p11}(s) - \dfrac{G_{p12}(s)G_{p21}(s)}{G_{p22}(s)} & 0 \\ 0 & G_{p22}(s) - \dfrac{G_{p12}(s)G_{p21}(s)}{G_{p11}(s)} \end{bmatrix} \tag{11}$$

Thus, the decoupled system is represented as

$$T_{11}(s) = \frac{G_{p11}(s)G_{p22}(s) - G_{p12}(s)G_{p21}(s)}{G_{p22}(s)} \tag{12}$$

$$T_{22}(s) = \frac{G_{p11}(s)G_{p22}(s) - G_{p12}(s)G_{p21}(s)}{G_{p11}(s)} \tag{13}$$

where, $T_{11}(s)$ and $T_{22}(s)$ represent the transfer functions for channel I (Flux) and channel II (Conductivity), respectively. Thus, decoupler will remove the interactions among input variables. The total decoupled scheme of the RO system is stable as each of subsystem block is open loop stable having negative real poles. Finally, the resulting scheme with feed-forward compensators is represented in Fig. 3. The PID controllers now can easily be tuned with different optimization algorithms even if one of the control loops is open.

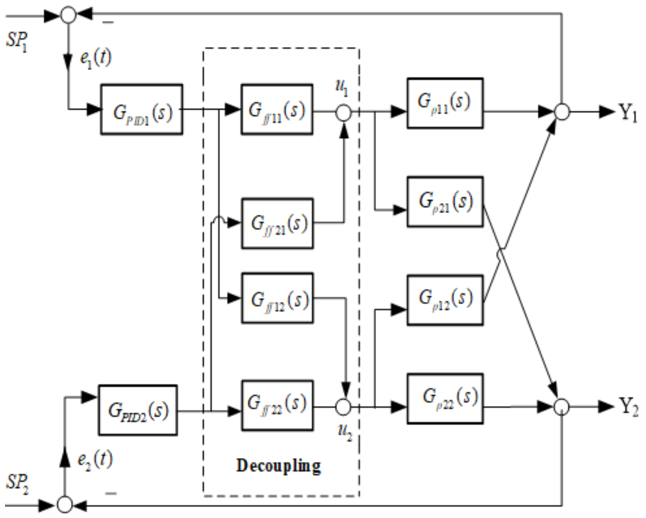

Fig. 2 Decoupling control system for RO system

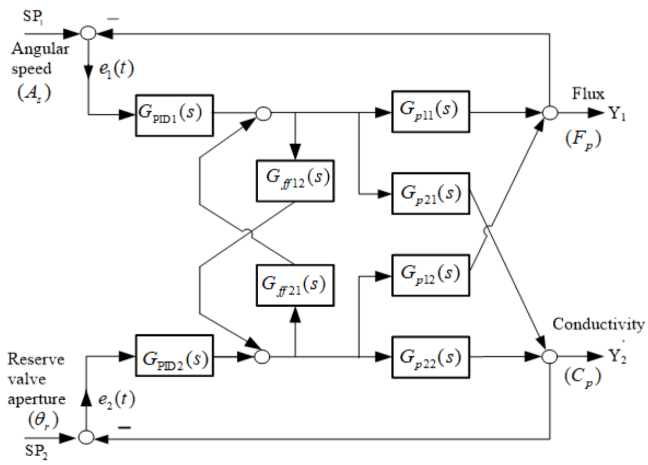

Fig. 3 Total decoupled scheme of an RO system with 2-PID controllers

4. Proposed scheme of optimal PID controller design

The goal of proposed optimal PID controller is to keep the water flux and water conductivity at desired value. A PID controller consists of proportional, integral and derivative gains. The feedback control system is illustrated in Fig. 4 where, $r(t)$ is reference input, $e(t)$ is the error between reference input and output variable, and $y(t)$ is controlled output variable. $G_{PID}(s)$ represents controller transfer function and $G_p(s)$ represents transfer function of the plant. The transfer function of PID controller, $G_{PID}(s)$, is given as

$$G_{PID}(s) = K_p + \frac{K_i}{s} + K_d s \quad (14)$$

where K_p, K_i and K_d are the proportional, integral and derivative gains, respectively, of the PID controller.

The set of controller parameters for the formation of objective function in RO model can be shown as

$$S = \begin{bmatrix} K_p & K_i & K_d \end{bmatrix} \quad (15)$$

The performance index is described as a quantitative measure to determine the system performance with the designed PID controller. This is used to design optimum system settings with adjusting the controller parameters to fulfil the specific design criteria in the system. In this work, ISE has been considered as a performance index for the problem due to its fast response and quick elimination of large errors.

In proposed scheme, TLBO based tuning of PID controller-parameters is carried out for the RO plant. The performance index of controller for channel I (Flux) can be evaluated by

$$J_1 = \int_0^\infty e_1^2(t)dt \quad (16)$$

J_1 is ISE. The Laplace transform of $e_1(t)$, obtained using Eq. (12), is given as

$$E_1(s) = \frac{n_5 s^5 + n_4 s^4 + n_3 s^3 + n_2 s^2 + n_1 s^1 + n_0}{d_6 s^6 + d_5 s^5 + d_4 s^4 + d_3 s^3 + d_2 s^2 + d_1 s^1 + d_0} \quad (17)$$

where, $n_0, n_1, n_2, \ldots n_5$ represent the numerator coefficients and $d_0, d_1, d_2, \ldots d_6$ represent the denominator coefficients (see Appendix B).

The ISE evaluated by Eq. (16) is determined from the generalized formula shown as follows

$$J_1 = \sum_{i=1}^{p_1} \frac{\beta_i^2}{2\alpha_i} \quad (18)$$

where the p_1 is the order of $E_1(s)$ and the parameters α_i and β_i are determined from the denominator and numerator coefficients of the $E_1(s)$ (Å ström 2012).

Furthermore, in a similar manner, the performance index J_2 for channel II (Conductivity) of RO model is determined as

$$J_2 = \int_0^\infty e_2^2(t)dt \quad (19)$$

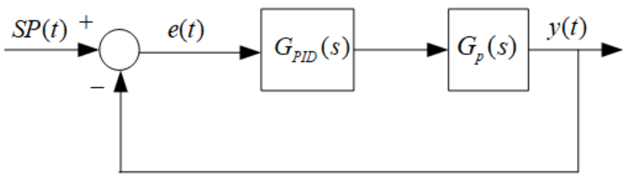

Fig. 4 A common feedback control system with PID controller

The Laplace transform of $e_2(t)$, obtained using Eq. (13), is represented as

$$E_2(s) = \frac{N_5 s^5 + N_4 s^4 + N_3 s^3 + N_2 s^2 + N_1 s^1 + N_0}{D_6 s^6 + D_5 s^5 + D_4 s^4 + D_3 s^3 + D_2 s^2 + D_1 s^1 + D_0} \quad (20)$$

where $N_0, N_1, N_2, \ldots N_5$ represent the numerator coefficients and $D_0, D_1, D_2, \ldots D_6$ represent the denominator coefficients (see Appendix C).

Now, the performance index J_2 can be determined as

$$J_2 = \sum_{i=1}^{p_2} \frac{B_i^2}{2A_i} \quad (21)$$

where, the p_2 is order of $E_2(s)$ and the parameters A_i and B_i are determined from the denominator and numerator coefficients of the $E_2(s)$ (Å ström 2012).

The performance indices are given by Eqs. (18) and (21) are minimized using TLBO, DE, ABC and PSO algorithms to show the comparative assessment. The details of TLBO algorithm is given in following section.

5. Teacher-learner-based-optimization

The tuning of PID controller-parameters is carried out with TLBO algorithm in this work. TLBO is newly introduced and quite popular metaheuristic algorithm. It is a population-based algorithm like other nature-inspired algorithms such as PSO, ABC, DE, etc., but unlike others, it does not possess any algorithm-specific parameters (Rao and Patel 2013). This algorithm takes into account the effect of influence of a best learner (teacher) onto the knowledge of other learners (students) in a class (or a group) and the knowledge gain of each learner through interaction. The total number of learners in a class constitutes the population and the total numbers of subjects offered are the decision variables. TLBO algorithm is mainly classified into two sections: the teacher phase and the learner phase.

5.1 Teacher phase

In this phase, the teacher tries to modify the results of the class based on his knowledge. The mean difference $\Delta M(n)$ between the existing mean, $M_j(n)$, and new mean of class at n^{th} iteration is given by

$$\Delta M(n) = r\left(X_{best,j}(n) - T_f \cdot M_j(n)\right) \quad (22)$$

where $X_{best,j}(n)$ represents the performance of the best learner (called as teacher) in j^{th} subject at n^{th} iteration, r is randomly generated number in the range [0,1] and T_f is teacher factor which is chosen as 1 or 2 (Rao *et al.* 2012). The value of T_f is obtained randomly with equal probabilities.

On the basis of mean difference, the new solution in the teacher phase is obtained as

$$\overline{X}_{i,j}(n) = X_{i,j}(n) + \Delta M(n) \quad (23)$$

where $\overline{X}_{i,j}(n)$ denotes the new value of the $X_{i,j}(n)$ at n^{th} iteration. Accept $\overline{X}_{i,j}(n)$ if it gives better performance index otherwise retain $\overline{X}_{i,j}(n)$ and obtain new solution, $Y_{i,j}(n)$, as

$$Y_{i,j}(n)=\begin{cases}\overline{X}_{i,j}(n) & \text{if } f\left(\overline{X}_{i,j}(n)\right)<f\left(X_{i,j}(n)\right)\\ X_{i,j}(n) & \text{if } f\left(\overline{X}_{i,j}(n)\right)>f\left(X_{i,j}(n)\right)\end{cases} \tag{24}$$

where $f\left(X_{i,j}(n)\right)$ and $f\left(\overline{X}_{i,j}(n)\right)$ are, respectively, the values of performance index for $X_{i,j}(n)$ and $\overline{X}_{i,j}(n)$.

Thus, obtained new solution $Y_{i,j}(n)$ is retained and used as input to the learner phase.

5.2 Learner phase

In learner phase, learners improve their knowledge by two methods: first through input from the teacher (or best learner) and second through interactions among themselves. In this way, the solution, $Y_{i,j}(n)$, obtained in teacher phase, is used as an input and the interaction between learners is kept random.

Further, select two learners, *a* and *b*, randomly such that $a \neq b$. Modify the solution according to Eq. (25) as

$$Z_{a,j}(n)=\begin{cases}\left[Y_{a,j}(n)+r_1\left(Y_{a,j}(n)-Y_{b,j}(n)\right)\right]\\ \qquad \text{if } f\left(Y_{a,j}(n)\right)<f\left(Y_{b,j}(n)\right)\\ \left[Y_{a,j}(n)+r_2\left(Y_{b,j}(n)-Y_{a,j}(n)\right)\right]\\ \qquad \text{if } f\left(Y_{b,j}(n)\right)>f\left(Y_{a,j}(n)\right)\end{cases} \tag{25}$$

where $Z_{a,j}(n)$ represents the modified solution obtained in learner phase, and $f\left(Y_{a,j}(n)\right)$ and $f\left(Y_{b,j}(n)\right)$ are the values of performance index for $Y_{a,j}(n)$ and $Y_{b,j}(n)$, respectively. The parameters r_1 and r_2 are two random numbers in the range [0,1]. Accept $Z_{i,j}(n)$ if it gives better performance index otherwise retain $Y_{i,j}(n)$. Thus obtained $Z_{i,j}(n)$ becomes input to the next iteration of teacher phase.

Repeat the above procedure of teacher phase and learner phase until the termination criterion is met.

The main steps of the TLBO are summarized in Fig. 5.

Experimental results and comparative assessments are given in the following section.

1. Initialize the population randomly
   //Teacher phase starts
2. Select the teacher
   Evaluate $f(X_{i,j})$
   Choose best learner (i.e. teacher)
   $X_{best} \leftarrow \text{best}(X_{i,j})$
3. Calculate teaching factor
   $T_f = \text{round}\ (1+\ \text{rand}\ (\ ))$
4. Calculate mean of class
   $M_j(n) \leftarrow \text{mean}(X_{i,j})$
5. Evaluate the mean difference
   $\Delta M(n) = r\left(X_{best,j}(n) - T_f . M_j(n)\right)$
6. Evaluate new value
   $\overline{X}_{i,j}(n) = X_{i,j}(n) + \Delta M_j(n)$
7. Select better solutions
   Evaluate $f(\overline{X}_{i,j})$
   if $\overline{X}_{i,j}$ is better than $X_{i,j}$, then
   $Y_{i,j} \leftarrow \overline{X}_{i,j}$
   else
   $Y_{i,j} \leftarrow X_{i,j}$
   end if
   //Teacher phase ends
   //Learner phase starts
8. Generate new solutions
   Choose two solutions, $Y_{a,j}$ and $Y_{b,j}$, randomly.
   if $f\left(Y_{a,j}(n)\right) < f\left(Y_{b,j}(n)\right)$, then
   $Z_{i,j} = Y_{a,j} + r_1.\left(Y_{a,j}(n) - Y_{b,j}(n)\right)$
   else
   $Z_{i,j} = Y_{a,j} + r_2.\left(Y_{b,j}(n) - Y_{a,j}(n)\right)$
   end if
9. Accept new solutions
   Evaluate $f(Z_{i,j})$
   Accept better solutions
10. Repeat 2-9 until the requirements are met.

Fig. 5 Main steps of TLBO algorithm

6. Experimental results and comparisons

To verify the efficiency of TLBO algorithm for PID controller tuning, two experiments, first minimization of ISE for channel I (Flux) of RO system and second minimization of ISE for channel II (Conductivity), have been performed. The common-control parameters and algorithm-specific parameters considered in experimentations are as follows.

6.1 Common-control parameters

The two common control parameters i.e., population size and maximum iteration number are set to 10 and 10, respectively, for all the four algorithms mentioned above in both the experiments.

6.2 Algorithm-specific parameters

TLBO settings: Except common parameters (i.e., population size and iteration numbers), no algorithm-specific parameter is required to be set in case of TLBO algorithm.

DE settings: In DE, mutation factor *F*=0.8, crossover rate *CR*=0.8 have been considered (Corne *et al.* 1999).

ABC settings: ABC algorithm employs one control parameter i.e., limit. It is denoted as limit=*SN***D* where *SN* is number of food sources and *D* is dimension of the problem (Karaboga and Akay 2009).

PSO settings: The inertia weight, cognitive factor, social factor, minimum velocity, maximum velocity are set to 0.5, 2, 2, -5 and 5, respectively, in the case of PSO (Trelea 2003).

Experiment 1: Minimization of ISE for Channel I (Flux)

In this experiment, performance index given by Eq. (18) is minimized to obtain the optimal values of PID controller gains i.e., K_{p1}, K_{i1}, and K_{d1}. Quantitative as well

Table 1 Values of PID gains for different algorithms for channel I (Flux)

Algorithms	K_{p1}	K_{i1}	K_{d1}
TLBO-PID	50.4540	-0.2016	1.0000
DE-PID	49.3316	16.3272	6.9678
ABC-PID	20.2817	19.4890	9.9771
PSO-PID	19.4279	6.7184	9.9088

Table 2 Comparisons of performance of different algorithms for channel I (Flux)

Performance measure	TLBO-PID	DE-PID	ABC-PID	PSO-PID
J_1 (Performance index)	2.3023E-05	0.1326	0.9542	4.7754
Rise Time	0.0336	0.2391	0.2895	0.3366
Settling Time	0.9646	3.8408	2.8090	5.8284
Overshoot (%)	0.0102	1.2554	1.9326	0.9689
Undershoot	0	0	0	0
Peak	1.0096	1.0126	1.0193	1.0096

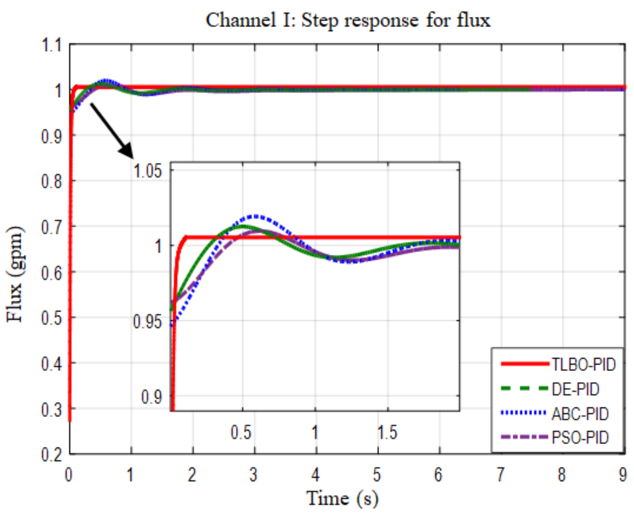

Fig. 6 Step response of flux (gpm) for channel I

Table 3 Values of PID gains for different algorithms for channel II (Conductivity)

Algorithms	K_{p2}	K_{i2}	K_{d2}
TLBO-PID	-200.0000	-12.6108	-6.8074
DE-PID	-141.8406	0.6859	-3.0184
ABC-PID	-188.9216	0.6022	-1.5198
PSO-PID	-192.5347	-36.3334	-5.3529

Table 4 Comparisons of performance of different algorithms for channel II (Conductivity)

Performance measure	TLBO-PID	DE-PID	ABC-PID	PSO-PID
J_2 (Performance index)	0.0012	0.0038	0.1545	0.0172
Rise Time	0.0182	0.1437	0.0996	0.1313
Settling Time	0.0247	5.1968	2.4703	2.5441
Overshoot (%)	0.1980	8.0394	6.3216	6.2678
Undershoot	0	0	0	0
Peak	1.0019	1.0801	1.0632	1.0626

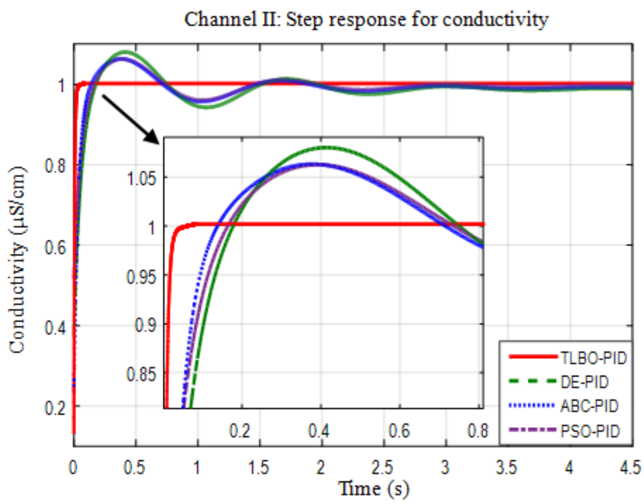

Fig. 7 Step response of conductivity(μS /cm) for channel II

as qualitative results are obtained which are shown in Tables 1 and 2 and Fig. 6. Table 1 shows the optimum values of PID gains obtained for channel I. Table 2 represents mean performance index. The value of the performance index for TLBO-PID is found to be 2.3023E-05 which is lowest when compared to other algorithms based PID controllers. In addition to performance index, time domain characteristics of step responses are also shown in Table 2. Numerical analysis of the results obtained shows that rise time, settling time and overshoot are lowest in case of TLBO-PID which is a good indication for a stable system. The plot of step responses using TLBO-PID, DE-PID, ABC-PID and PSO-PID is shown in Fig. 6. The superiority in terms of performance index and time domain analysis indicates the successful implementation of TLBO algorithm for PID controller tuning of RO unit.

Experiment 2: Minimization of ISE for Channel II (Conductivity)

In the second experiment, performance index given by Eq. (21) is minimized to obtain the optimal values of PID controller gains i.e., K_{p2}, K_{i2}, and K_{d2}. All the four algorithms i.e., TLBO, DE, ABC, and PSO are implemented for same criterion. Quantitative as well as qualitative results are obtained from these algorithms are shown in Tables 3 and 4.

Table 3 shows the optimum values of PID gains obtained using TLBO, DE, ABC and PSO. Table 4 gives the performance index comparisons and time domain specifications. The value of performance index is lowest for TLBO-PID when compared to DE-PID, ABC-PID and PSO-PID in all the cases. In addition to performance index, time domain characteristics i.e., rising time, settling time, overshoot, undershoot and peak value calculated from step response have also been improved. The step response plot obtained for all these algorithms is shown in Fig. 7.

7. Conclusions

In this work optimal PID controller tuning is presented using teacher-learner-based-optimization (TLBO) for reverse osmosis (RO) desalination plant. The simplified decoupling technique has been used for designing feed-forward compensator for RO transfer function model. ISE is considered as performance index for tuning of controller parameters. Two experiments, one for channel I and second for channel II of RO plant, were performed. The performance of TLBO algorithm is verified with the well-known optimizing techniques such as particle swarm optimization (PSO), artificial bee colony (ABC), and deferential evolution (DE) algorithms. The experimental results show the superiority of TLBO-PID over PSO-PID, ABC-PID, and DE-PID. Future scope of this research lies in the design of TLBO based robust PID controller for RO desalination plants. Additionally, a multi-objective design for RO can also be investigated using TLBO algorithm.

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Appendix A

The model parameters for unit RO system are considered as (Chaaben *et al.* 2011)

$$k_{11} = 2.50,\ k_{22} = -0.20,\ \tau_{11} = 1.00,\ \tau_{22} = 1.00,\ \omega_{11} = 1.50,$$
$$\omega_{22} = 2.15,\ \xi_1 = 0.50,\ \xi_2 = 0.75,\ \text{and}\ \ r_1 = r_2 = 1$$

Appendix B

Numerator coefficients of $E_1(s)$ are given as

$$\begin{aligned}
n_5 &= k_{22} r_1 \tau_{11};\\
n_4 &= k_{22} r_1 + 2k_{22} r_1 \tau_{11}\omega_1\xi_1 + 2k_{22} r_1 \tau_{11}\omega_2\xi_2;\\
n_3 &= k_{22} r_1 \tau_{11}\omega_1^2 + 4k_{22} r_1 \tau_{11}\xi_1\xi_2\omega_1\omega_2 + 2k_{22} r_1\xi_1\omega_1 + k_{22} r_1 \tau_{11}\omega_2^2 + 2k_{22} r_1\xi_2\omega_2;\\
n_2 &= 2k_{22} r_1 \tau_{11}\xi_2\omega_1^2\omega_2 + k_{22} r_1\omega_1^2 + 2k_{22} r_1 \tau_{11}\xi_1\omega_1\omega_2^2 + 4k_{22} r_1\xi_1\xi_2\omega_1\omega_2 + k_{22} r_1\omega_2^2;\\
n_1 &= k_{22} r_1 \tau_{11}\omega_1^2\omega_2^2 + 2k_{22} r_1\xi_2\omega_1^2\omega_2 + 2k_{22} r_1\xi_1\omega_1\omega_2^2;\\
n_0 &= k_{22} r_1\omega_1^2\omega_2^2;
\end{aligned}$$

Denominator coefficients of $E_1(s)$ are given as

$$\begin{aligned}
d_6 &= k_{22}\tau_{11} + k_{11}k_{22}K_{d1};\\
d_5 &= k_{22} + k_{11}k_{22}K_{p1} + 2k_{22}\tau_{11}\omega_1\xi_1 + 2k_{22}\tau_{11}\omega_2\xi_2 + 2k_{11}k_{22}K_{d1}\omega_1\xi + 2k_{11}k_{22}K_{d1}\omega_2\xi_2;\\
d_4 &= k_{11}k_{22}K_{i1} + 2k_{22}\omega_1\xi_1 + 2k_{22}\omega_2\xi_2 + k_{22}\tau_{11}\omega_1^2 + k_{22}\tau_{11}\omega_2^2 + k_{11}k_{22}K_{d1}\omega_1^2 + k_{11}k_{22}K_{d1}\omega_2^2 - K_{d1}\tau_{11}\tau_{22}\omega_1^2\omega_2^2\\
&\quad + 2k_{11}k_{22}K_{p1}\omega_2^2\xi_2 + 2k_{11}k_{22}K_{p1}\omega_2\xi_2 + 4k_{22}\tau_{11}\omega_1\omega_2\xi_1\xi_2 + 4k_{22}K_{d1}\omega_1\omega_2\xi_1\xi_2;\\
d_3 &= k_{22}\omega_1^2 + k_{22}\omega_2^2 - K_{d1}\tau_{11}\omega_2^2\omega_2^2 - K_{d1}\tau_{22}\omega_2^2\omega_2^2 + k_{11}k_{22}K_{p1}\omega_1^2 + k_{11}k_{22}K_{p1}\omega_2^2 + 4k_{22}\omega_1\omega_2\xi_1\xi_2 + 2k_{22}\tau_{11}\omega_1\omega_2^2\xi_1\\
&\quad + 2k_{22}\tau_{11}\omega_1^2\omega_2\xi_2 - K_{p1}\tau_{11}\tau_{22}\omega_1^2\omega_2^2 + 2k_{11}k_{22}K_{i1}\omega_2\xi_1 + 2k_{11}k_{22}K_{i1}\omega_2\xi_2 + 2k_{11}k_{22}K_{d1}\omega_1\omega_2^2\xi_1\\
&\quad + 2k_{11}k_{22}K_{d1}\omega_1^2\omega_2\xi_2 + 4k_{11}k_{22}K_{p1}\omega_1\omega_2\xi_1\xi_2;\\
d_2 &= 2k_{22}\omega_1\omega_2^2\xi_1 - K_{d1}\omega_1^2\omega_2^2 + 2k_{22}\omega_1^2\omega_2\xi_2 + k_{22}\tau_{11}\omega_1^2\omega_2^2 - K_{p1}\tau_{11}\omega_1^2\omega_2^2 - K_{p1}\tau_{22}\omega_1^2\omega_2^2 + k_{11}k_{22}K_{i1}\omega_1^2 + k_{11}k_{22}K_{i1}\omega_2^2\\
&\quad + k_{11}k_{22}K_{d1}\omega_1^2\omega_2^2 - K_{i1}\tau_{11}\tau_{22}\omega_1^2\omega_2^2 + 2k_{11}k_{22}K_{p1}\omega_1\omega_2^2\xi_1 + 2k_{11}k_{22}K_{p1}\omega_1^2\omega_2\xi_2 + 4k_{11}k_{22}K_{i1}\omega_1\omega_2\xi_1\xi_2;\\
d_1 &= k_{22}\omega_1^2\omega_2^2 - K_{p1}\omega_1^2\omega_2^2 - K_{i1}\tau_{11}\omega_1^2\omega_2^2 - K_{i1}\tau_{22}\omega_1^2\omega_2^2 + k_{11}k_{22}K_{p1}\omega_1^2\omega_2^2 + 2k_{11}k_{22}K_{i1}\omega_1\omega_2^2\xi_1 + 2k_{11}k_{22}K_{i1}\omega_1^2\omega_2\xi_2;\\
d_0 &= k_{11}k_{22}K_{i1}\omega_1^2\omega_2^2 - K_{i1}\omega_1^2\omega_2^2;
\end{aligned}$$

Appendix C

Numerator coefficients of $E_2(s)$ are given as

$$\begin{aligned}
N_5 &= k_{11} r_2 \tau_{22};\\
N_4 &= k_{11} r_2 + 2k_{11} r_2\omega_1\xi_1 + 2k_{11} r_2 \tau_{22}\omega_2\xi_2;\\
N_3 &= k_{11} r_2 \tau_{22}\omega_1^2 + 4k_{11} r_2 \tau_{22}\xi_1\xi_2\omega_1\omega_2 + 2k_{11} r_2\xi_1\omega_1 + k_{11} r_2 \tau_{22}\omega_1^2 + 2k_{11} r_2\xi_2\omega_2;\\
N_2 &= 2k_{11} r_2 \tau_{22}\xi_2\omega_1^2\omega_2 + k_{11} r_2\omega_1^2 + 2k_{11} r_2 \tau_{22}\xi_1\omega_1\omega_2^2 + 4k_{11} r_2\xi_1\xi_2\omega_1\omega_2 + k_{11} r_2\omega_2^2;\\
N_1 &= k_{11} r_2 \tau_{22}\omega_1^2\omega_2^2 + 2k_{11} r_2\xi_2\omega_1^2\omega_2 + 2k_{11} r_2\xi_1\omega_1\omega_2^2;\\
N_0 &= k_{11} r_2\omega_1^2\omega_2^2;
\end{aligned}$$

Denominator coefficients of $E_2(s)$ are given as

$$\begin{aligned}
D_6 &= k_{11}\tau_{22} + k_{11}k_{22}K_{d2};\\
D_5 &= k_{11} + k_{11}k_{22}K_{p2} + 2k_{11}k_{22}\tau_{22}\omega_1\xi_1 + 2k_{11}\tau_{22}\omega_2\xi_2 + 2k_{11}K_{d2}\omega_1\xi_1 + 2k_{11}k_{22}K_{d2}\omega_2\xi_2;\\
D_4 &= k_{11}k_{22}K_{i2} + 2k_{11}\omega_1\xi_1 + 2k_{11}\omega_2\xi_2 + k_{11}\tau_{22}\omega_1^2 + k_{11}\tau_{22}\omega_2^2 + k_{11}k_{22}K_{d2}\omega_1^2 + k_{11}k_{22}K_{d2}\omega_2^2\\
&\quad - K_{d2}\tau_{11}\tau_{22}\omega_1^2\omega_2^2 + 2k_{11}k_{22}K_{p2}\omega_1\xi_1 + 2k_{11}k_{22}K_{p2}\omega_2\xi_2 + 4k_{11}\tau_{22}\omega_1\omega_2\xi_1\xi_2 + 4k_{11}k_{22}K_{d2}\omega_1\omega_2\xi_1\xi_2;\\
D_3 &= k_{22}\omega_2^2 + k_{11}\omega_2^2 - K_{d2}\tau_{11}\omega_1^2\omega_2^2 - K_{d2}\tau_{22}\omega_1^2\omega_2^2 + k_{11}k_{22}K_{p2}\omega_1^2 + k_{11}k_{22}K_{p2}\omega_2^2 + 4k_{11}\omega_1\omega_2\xi_1\xi_2\\
&\quad + 2k_{11}\tau_{22}\omega_1\omega_2^2\xi_1 + 2k_{11}\tau_{22}\omega_1^2\omega_2\xi_2 - K_{p2}\tau_{11}\tau_{22}\omega_1^2\omega_2^2 + 2k_{11}k_{22}K_{i2}\omega_1\xi_1 + 2k_{11}k_{22}K_{i2}\omega_2\xi_2\\
&\quad + 2k_{11}k_{22}K_{d2}\omega_1\omega_2^2\xi_1 + 2k_{11}k_{22}K_{d2}\omega_1^2\omega_2\xi_2 + 4k_{11}k_{22}K_{p2}\omega_1\omega_2\xi_1\xi_2;\\
D_2 &= 2k_{22}\omega_1\omega_1^2\xi_1 - K_{d2}\omega_1^2\omega_2^2 + 2k_{11}\omega_1^2\omega_2\xi_2 + k_{11}\tau_{22}\omega_1^2\omega_2^2 - K_{p2}\tau_{11}\omega_1^2\omega_2^2 - K_{p2}\tau_{22}\omega_1^2\omega_2^2 + k_{11}k_{22}K_{i2}\omega_1^2\\
&\quad + k_{11}k_{22}K_{i2}\omega_2^2 + k_{11}k_{22}K_{d2}\omega_1^2\omega_2^2 - K_{i2}\tau_{11}\tau_{22}\omega_1^2\omega_2^2 + 2k_{11}k_{22}K_{p2}\omega_1\omega_2^2\xi_1 + +2k_{11}k_{22}K_{p2}\omega_1^2\omega_2\xi_2 + 4k_{11}k_{22}K_{i2}\omega_1\omega_2\xi_1\xi_2;\\
D_1 &= k_{11}\omega_1^2\omega_2^2 - K_{p2}\omega_1^2\omega_2^2 - K_{i2}\tau_{11}\omega_1^2\omega_2^2 - K_{i2}\tau_{22}\omega_1^2\omega_2^2 + k_{11}k_{22}K_{p2}\omega_1^2\omega_2^2 + k_{11}k_{22}K_{i2}\omega_1\omega_2^2\xi_1 + 2k_{11}k_{22}K_{i2}\omega_1^2\omega_2\xi_2;\\
D_0 &= k_{11}k_{22}K_{i2}\omega_1^2\omega_2^2 - K_{i2}\omega_1^2\omega_2^2;
\end{aligned}$$