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Multiple-loop PI Controller Design for TITO System using Teaching Learning Based Optimization

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Abstract

Background/Objectives: The major objective of this work is to propose PI controller tuning for Two Input Two Output (TITO) process models using the Teaching Learning Based Optimization (TLBO) algorithm. **Methods/Statistical analysis:** In this work, the dimension of the heuristic search is assigned as four (Kp1, Ki1, Kp2, Ki2). A weighted sum of objective function is considered in order to achieve the optimal controller values. The proposed method is tested using the Wardle and Wood model and Vinante and Luybenmodel. The efficiency of the proposed method has been validated through a comparative study with the PSO, BFO and FA existing in the literature. **Findings:** The result confirms that, TLBO tuned controller offers better result compared with other heuristic methods considered in this study for both the reference tracking and disturbance rejection operations. **Applications/Improvements:** In future, this method can be implemented for 2x2 and 3x3 MIMO systems existing in literature.

Keywords: Distillation Process, PI Controller, TITO Model, TLBO Algorithm, Validation

1. Introduction

In chemical process industries, most of the important processes are multivariable in nature. Distillation is one of these paration process widely implemented in the petroleum and chemical industries for purification of final products. Due to its industrial significance, the distillation column is one of the generally chosen very important multivariable processes by the researchers[1-7].

Controller design process for the stable, unstable and non-linear single input single output systems are simple compared with the Two Input Two Output (TITO) systems. Hence, due to its complexity, the numbers of controller design procedures available for TITO systems are very small compared to single input single output systems.

The control literature presents the traditional and modern approach based design and implementation of the PI/PID controllers for a class of systems[8-18]. In this paper, PI controller design for TITO is addressed. The existing controller design procedure for TITO process can be categorized as 1. Centralized and 2. Decentralized methods. In centralized system, controller design task is quite complex compared with the decentralized system due to the interaction between the loops. In the proposed work, heuristic algorithm assisted centralized PI controller deign is discussed for the TITO systems existing in the literature.

In this paper, recent heuristic method, known as Teaching Learning Based Optimization (TLBO) technique proposed[19,20] is adopted to solve the controller design problem. This algorithm is theoretically similar to the teaching-learning scenario existing in the class room learning process. In order to obtain best optimal value, the controller design process is repeated 10 times and the mean of controller values, such as K_{p1}, K_{i1}, K_{p2}, K_{i2} are recorded. The simulation study is carried out using the Matlab software and the performance of the proposed method is validated with Particle Swarm Optimization (PSO), Bacterial Foraging Optimization (BFO) and Firefly Algorithm (FA) existing in the literature. In order to execute a fair comparison, all the algorithms are

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assigned with similar population size, iteration number, stopping criteria and objective function.

The remaining sections of this paper are arranged as follows. Section 2 describes the distillation process and its bench mark versions. Section 3 presents the overview of the TLBO algorithm considered in this study, the simulated results of this work is presented in section 4 and the conclusion of the present work is discussed in section 5.

2. Process Description

In chemical and petroleum industries, distillation is the separation methodology used to convert the raw mixtures in to usable final products. The mixture is applied on the distillation column, with a number of trays and a number of temperature regions. Based on the column temperature, the mixture is split into the Liquid (L) and the Vapour (V) products. The process for the distillation column is based on L-V structure or the energy balance method. In this control configuration, the vapour flow rate and the liquid flow rate are the control inputs[5-7].

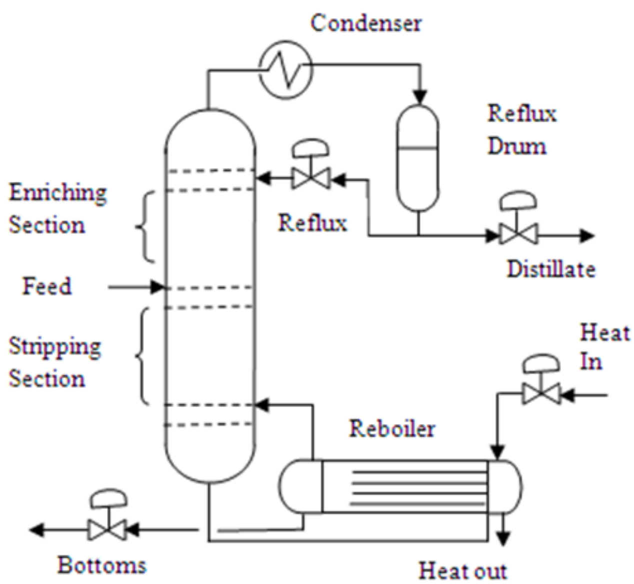


Figure 1. Schematic of distillation column.

Figure 1 shows the schematic of the industrial scale distillation column. In this paper the benchmark distillation columns, such as WW and VL are chosen.

Figure 2 shows the structure of TITO centralized control system. In this work, the controllers in TP loop (PI_1) and BP loop (PI_2) are designed using TLBO algorithm.

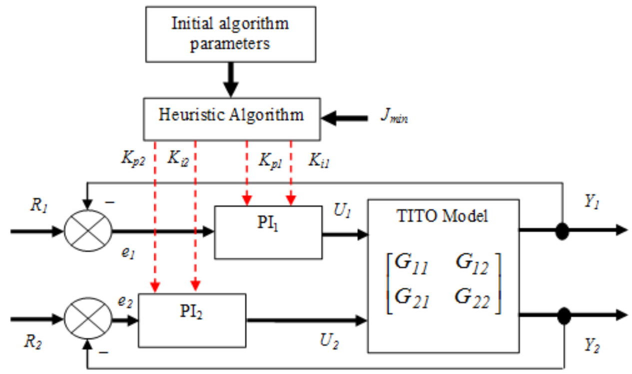


Figure 2. Schematic of centralised controller design for TITO process.

The parallel form of PI controller adopted in this system is presented in Equation 1 and 2.

$$PI_1 = K_{p1} + \frac{K_{i1}}{s} \tag{1}$$

$$PI_2 = K_{p2} + \frac{K_{i2}}{s} \tag{2}$$

In this, the PI controllers are responsible for the final product quality of Y_1 and Y_2. Hence, it is necessary to find optimal values for the controllers.

The WW model[4] and VL model[5,6] considered in this work is presented in Equation 3 and 4.

$$G(s) = \begin{bmatrix} \frac{0.126}{60s+1}e^{-6s} & \frac{-0.101}{(48s+1)(45s+1)}e^{-12s} \\ \frac{0.094}{38s+1}e^{-8s} & \frac{-0.12}{35s+1}e^{-8s} \end{bmatrix} \tag{3}$$

$$G(s) = \begin{bmatrix} \frac{-2.2}{7s+1}e^{-s} & \frac{1.3}{7s+1}e^{-0.3s} \\ \frac{-2.8}{9.5s+1}e^{-1.8s} & \frac{4.3}{9.2s+1}e^{-0.35s} \end{bmatrix} \tag{4}$$

In the proposed work, PI_1 and PI_2 are designed to support the reference tracking and disturbance rejection operations based the set points R_1 and R_2.

3. Teaching Learning Based Optimization

TLBO is formulated by imitating the teaching-learning system existing in the classroom scenario and its pseudo code is depicted below. Similar to other heuristic algorithms, the TLBO employs a population based approach to attain the collective explanation during the exploration. A complete clarification about the TLBO can be found in the recent literature[19-22]. In this work, conventional TLBO is adopted to tune the PI controllers for the TITO process.

The TLBO has two necessary stages, such as teacher stage and learner stage as shown below:

START;

Initialize algorithm parameters, such as number of learners (N), parameters to be optimized (D), Maximum number of iteration (Miter) and objective function (J_{min}); Randomly initialize 'N' learners for x_i (i = 1, 2, … n);
Evaluate the performance and select the best solution f(x_{best});
WHILE iter = 1:Miter;
%TEACHER STAGE %
Use f(x_{best}) as teacher;
Sort based on f(x), select other teachers based on : f(x)$_s$ = f(x_{best}) – rand for f(x)$_s$ = 2,3, . . . , T;
FOR i = 1:n
Calculate $T_F^i = round[1 + rand(0,1)\{2-1\}]$;
$x_{new}^i = x^i + rand(0,1)[x_{teacher} - (T_F^i . x_{mean})]$,
%Calculate objective function for $f(x^i_{new})$%
If $f(x^i_{new}) < f(x_i)$, then $x^i = x^i_{new}$;
End If % End of TEACHER STAGE%
%STUDENT STAGE %
Arbitrarily Select the learner x^i, such that j ≠ i;
If $f(x^i) < f(x^j)$, then $x^i_{new} = x^i + rand(0,1)(x^i - x^j)$;
Else $x^i_{new} = x^i + rand(0,1)(x^j - x^i)$;
End If
If x^i_{new} *is better than* x^i, *then* $x^i = x^i_{new}$;
End If % End of STUDENT STAGE%
End FOR
Set k = k+1;
End WHILE
Record the controller valus, J_{min}, and performance measures;
STOP;

In this work, heuristic algorithms such as Particle Swarm Optimization (PSO) and Firefly Algorithm (FA) are considered to validate the performance of TLBO.

- **Particle Swarm Optimization**

PSO is developed by modeling the group activities in flock of birds or school of fish. Due to its high computational capability, it is widely considered by the researches to solve constrained and unconstrained optimization problems. In this work, PSO with the following mathematical expression is considered[23]:

$$V_i(t+1) = W^t . V_i^t + C_1 R_1 (P_i^t - S_i^t) + C_2 R_2 (G_i^t - S_i^t) \quad (5)$$

$$X_i(t+1) = X_i^t + V_i(t+1) \quad (6)$$

where w^t is inertia weight (chosen as 0.6), R_1 and R_2 are random values [0,1], C_1 and C_2 is allotted as 2.0 and 1.5 correspondingly.

- **Bacterial Foraging Optimization**

Bacterial Foraging Optimization (BFO) algorithm is one of the successful nature inspired heuristic method, developed based on the mathematical model of the foraging activities in Escherichia coli (E.coli) bacteria. In this work, the enhanced BFO algorithm discussed in[10-13] is adopted.

$$N = 30; N_c = \frac{N}{2}; N_s = N_{re} \approx \frac{N}{3}; N_{ed} \approx \frac{N}{4}; N_r = \frac{N}{2}; P_{ed} = \left(\frac{N_{ed}}{N + N_r}\right);$$
$$d_{attract} = W_{attract} = \frac{N_s}{N}; \ and \ h_{repell} = W_{repell} = \frac{N_c}{N} \quad (7)$$

- **Firefly Algorithm**

FA based technique utilizes the mathematical representation of a firefly, searching for a mate in the assigned search space. The detail of FA can be found in[24]. The association of an attracted firefly towards a mate can be expressed as:

$$X_i^{t+1} = X_i^t + \beta_0 e^{-\gamma d_{ij}^2} (X_j^t - X_i^t) + \alpha^1 (rand - 1/2) \quad (8)$$

where X_i^t is early location; X_i^{t+1} is updated location; $\beta_0 e^{-\gamma d_{ij}^2}(X_j^t - X_i^t)$ is attraction among fireflies; β_0 is preliminary attractiveness; γ is absorption coefficient; α^1 is randomization operator and rand is random number [0,1]. In this paper, the following values are chosen for FA parameters: α^1 = 0.15; β_0 = 0.1and γ = 1.

4. Result and Discussions

The controller design problem deals with finding optimal values of K_p and K_i for the top and bottom process loops. In this work, the TLBO explores the four dimensional search space in order to find the optimal controller values. For the controller design problem, a weighted sum of cost function is assigned to guide the heuristic search as given below.

$$J_{\min} = W_1 . M_p + W_2 . t_s + W_3 . ISE + W_4 . \text{IAE} \quad (9)$$

where M_p is peak overshoot, t_s is settling time, ISE is integral squared error and IAE is integral absolute error. The weights are assigned as $W_1 = W_2 = 5$ and $W_3 = W_4 = 10$.

The problem of assigning the optimal parameters for multi-loop PI controllers which stabilise TITO system is addressed in the paper. A centralised PI controller design procedure is implemented on some well known bench mark systems, such as WW and VL model. A comparative study among the heuristic algorithms, such as PSO, BFO and FA are presented.

The heuristic algorithm based search continuously explores the four dimensional search universe until the cost function is minimized. For all the heuristic algorithms, the population size is assigned as 30 and maximum iteration number is chosen as 500 and the stopping criterion is chosen as J_{min}.

Initially the proposed work is tested on the WW distillation column model. In this work, the optimization exploration is repeated 10 times with each considered heuristic algorithm and the mean value among the trial is chosen as the optimal controller parameter.

Table 1 presents the controller values obtained with the heuristic algorithms for WW and VL processes.

Table 1. Optimal controller values and corresponding iteration number

Process	Method	PI_1		PI_2		Average Iteration
		K_{p1}	K_{i1}	K_{p2}	K_{i2}	
WW	PSO	-1.0345	-0.4149	2.3552	0.3067	268
	BFO	-0.9566	-0.5088	1.9903	0.4028	302
	FA	-0.8879	-0.5024	2.1887	0.4022	275
	TLBO	-1.0041	-0.4353	2.0881	0.4159	274
VL	PSO	-1.2270	-0.0882	2.7112	0.3975	249
	BFO	-1.5033	-0.1162	2.3938	0.4174	337
	FA	-1.1977	-0.1225	2.9003	0.7034	258
	TLBO	-1.0106	-0.0958	2.8113	0.5470	252

Initially a unity setpoint is applied for the top product (r_1) by keeping the other input (r_2) as zero. A disturbance of 0.3 (30% of set point) is then applied at 100 sec. From Figure 3(a) and 3(b), it can be observed that, the proposed method offers better result. From Table 2, it can be noted that, TLBO approach offers better M_p and t_s value for the top product loop and t_s, ISE and IAE for the bottom product loop for WW model compared to PSO, BFO and FA.

Then, similar procedure is repeated on the VL model with unity setpoint on the bottom product (r_2) by keeping the other input (r_1) as zero. A disturbance of 0.3 (30% of set point) is then applied at 150 sec. From Figure 4(a) and 4(b), it can be observed that, the proposed method outperforms the PSO and BFO algorithms.

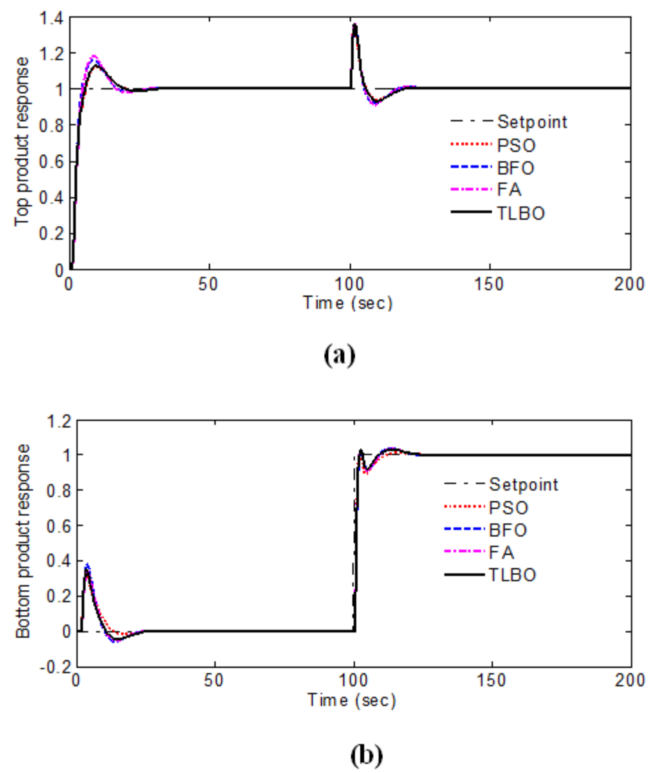


Figure 3. (**a**) Disturbance rejection performance of WW model (**b**) Bottom product loop response of WW model.

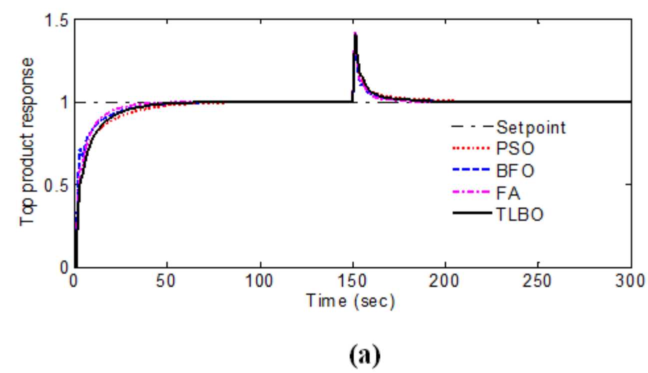
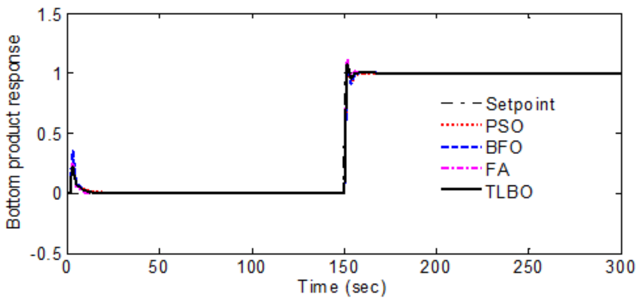


Table 2. Performance measures obtained for disturbance rejection

Process	Method	Top product				Bottom product			
		M_p	t_s	ISE	IAE	M_p	t_s	ISE	IAE
WW	PSO	**0.127**	**23.74**	1.544	1.242	**0.330**	30.72	0.113	0.336
	BFO	0.160	20.81	**1.026**	**1.013**	0.379	27.04	0.065	0.256
	FA	0.186	20.06	1.053	1.025	0.345	26.88	0.066	0.255
	TLBO	**0.127**	**23.74**	1.402	1.184	0.350	**25.18**	0.061	**0.247**
VL	PSO	0.000	**51.27**	34.163	5.845	0.351	22.57	0.067	0.259
	BFO	0.000	53.34	19.682	4.436	0.269	34.02	0.061	0.247
	BA	0.000	56.02	**17.715**	**4.208**	0.255	**12.84**	0.022	0.146
	TLBO	0.000	58.71	28.951	5.381	**0.226**	21.79	0.036	0.188



(b)

Figure 4. (**a**) Disturbance rejection performance of VL model (**b**) Bottom product loop response of VL model.

5. Conclusion

The problem of finding the best possible controller parameters for TITO system using TLBO algorithm is discussed in this paper. Proposed centralised PI controller design procedure is tested using some well known bench mark distillation column, such as WW and VL model. This study shows that, the proposed PI controller design procedure offers better performance measure values for the reference tracking and disturbance rejection operations compared with the alternatives considered in this work.

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