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Bio inspired technique for controlling angle of attack of aircraft

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ABSTRACT

This paper deals with the design of a proportional–integral (PI) controller for controlling the angle of attack of flight control system. For the first time teaching learning-based optimization (TLBO) algorithm is applied in this area to obtain the parameters of the proposed PI controller. The design problem is formulated as an optimization problem and TLBO is employed to optimize the parameters of the PI controller. The superiority of proposed approach is demonstrated by comparing the results with that of the conventional methods like genetic algorithm (GA) and particle swarm optimization (PSO). It is observed that TLBO optimized PI controller gives better dynamic performance in terms of settling time, overshoot, and undershoot as compared to GA and PSO based PI controllers. The various performance indices like mean square error (MSE), integral absolute error (IAE), and integral time absolute error (ITAE) are improved by using the TLBO soft computing techniques. Further, robustness of the system is studied by varying all the system parameters from −50% to +50% in step of 25%. Analysis also reveals that TLBO optimized PI controller gains are quite robust and need not be reset for wide variation in system parameters.

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1. INTRODUCTION

For smooth flying of an aircraft, managing of three controlling surfaces viz rudder, elevator, and aileron becomes inevitable. The movement of a flight is controlled by the help of above three surfaces about the pitch, roll, and yaw axes. For the orientation of aircraft, elevator performs an essential position in changing the angle of attack along with pitch. Different soft computing techniques like fuzzy model reference learning (FMRL) and radial basis function neural controller (RBFNC) are applied previously for obtaining a better result for a dynamic system. But a new soft computing technique named teaching learning-based optimization (TLBO) is incorporated in this paper mainly for adjusting the angle of attack as well as upgrading the overall achievement of the proposed system. Finally, a comparison is made between the results of TLBO and other optimization methods like genetic algorithm (GA) and particle swarm optimization (PSO) in each and every aspect.

Literature survey reveals most of the early works on flight control system. The selection of gain of a proportional–integral (PI) controller for nonlinear second order plants was suggested by Kumar *et al.* [1] in an organized manner. The regulating of a PI controller for a control system was verified by Xiang *et al.* [2] in a number of ways. A better proposal was proposed by Saxena and Hote [3] for determining the gain of a PI controller. An easy and quick method for tuning a proportional–integral–derivative (PID) controller was jointly analyzed by Ghany *et al.* [4] in a precise manner. The various types of methods needed for estimating the angle of attack of a flight were clearly described by Sankaralingam and Ramprasadh [5]. Two-stage TLBO method for flexible job-shop scheduling was suggested by Buddala and Mahapatra [6]. Suganthi *et al.* [7] proposed an improved TLBO algorithm. Niu *et al.* [8] suggested a modified TLBO algorithm for numerical function optimization. Shahrouzi *et al.* [9] suggested a hybrid bat algorithm and TLBO.

Zhai *et al.* [10] proposed a novel TLBO with error correction for path planning of unmanned air vehicle. Zhang *et al.* [11] suggested an improved TLBO with logarithmic spiral and triangular mutation for global optimization. Nayak *et al.* [12] proposed an Elitist teaching–learning-based optimization (ETLBO) with higher-order Jordan Pi-sigma neural network. Yang *et al.* [13] proposed a multiobjective GA on an accelerator lattice. In addition, Gaing [14] proposed a PSO method to solve the economic dispatch. Evtushenko and Posypkin [15] suggested a new method in 2013 for global box-constrained optimization. Yassami and Ashtari [16] proposed a novel hybrid optimization algorithm. Storn and Price [17] proposed a diferential evolution for global optimization over continuous spaces. A fuzzy adaptive diferential evolution algorithm. on soft computing was suggested by. Liu and Lampinen [18]. Several researchers proposed on ant colony optimization [19], [20].

Placement of wind turbines using GA was suggested by Grady *et al.* [21]. Graphic processing unit (GPU)-based parallel PSO was proposed by Zhou and Tan [22]. A survey on new generation metaheuristic algorithms was jontly suggested in 2019 by Dokeroglu *et al.* [23]. Hussain *et al.* [24] did a comprehensive survey on artificial intelligence review. Various works on PSO using different techniques ware proposed in [25]–[28]. PSO-based memetic algorithm for fow shop scheduling was suggested by Liu *et al.* [29]. Yang *et al.* [30] suggested an improved PSO-based charging strategy of electric vehicles in electrical distribution grid. This paper shows a better result by applying TLBO method for managing the attacking angle of an air craft system. After comparison the results between TLBO, GA and PSO methods, it was found that TLBO performs better in all aspects than GA and PSO methods for tuning the PID controller.

2. BLOCK DIAGRAM FOR DETERMINING THE ANGLE OF ATTACK

Figure 1 shows the block diagram for controlling the angle of attack of an aircraft. The intended angle of attack (α) is the output. The elevator's deflection (δ_E) serves as the input.

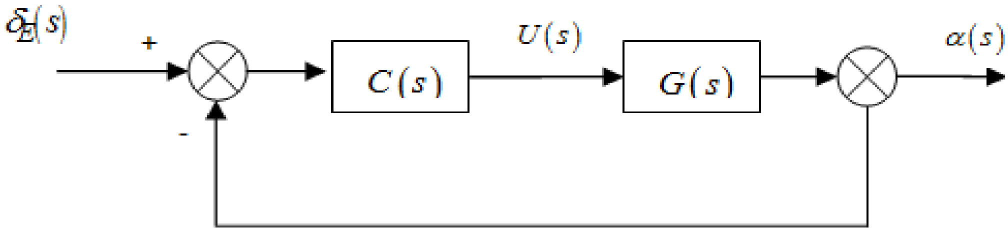

Figure 1. Schematic diagram of angle of attack for an aircraft system

where $\delta_E(s)$ is the deflection angle of elevator, $\alpha(s)$ is angle of attack of the aircraft, *G*(s) is the forward path gain, and *C*(s) is proposed PI controller.

3. RELATION BETWEEN THE ELEVATOR DEFLECTION (δ_E) AND ANGLE OF ATTACK (α)

Generally, angle of attack is the angle between relative wind and the chord line of the aircraft. The angle of attack is obtained due to the deflection in control surface (elevator) is exhibited in Figure 2. Aircraft speed (u), is changed due to the deflection in control surfaces and atmospheric turbulence. Mainly the approximation relating to short period deals with varying flight speed (u) and it consists of very short duration. The speed of the aircraft U_0 almost remains constant throughout the process i.e., $u = 0$. So that the motion related equation involving $'u'$ is generally neglected. Hence the equations for longitudinal motion may be dictated as:

$$\dot{w} = Z_w w + U_0 q + Z_{\delta_s} \delta_E \tag{1}$$

$$\boldsymbol{q = M_{\dot{w}}w + M_w\dot{w} + M_q q + M_{\delta_z}\delta_E} \qquad (2)$$
$$= (M_{\dot{w}} + M_w Z_w)w + (M_q + U_0 M_w)q + (M_{\delta_z} + Z_{\delta_z} M_{\dot{w}})\delta_E$$

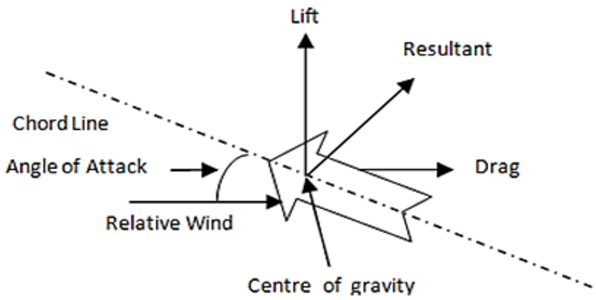

Figure 2. Description of angle of attack

Calculation of state vector for short period motion may be written as:

$$x = \begin{bmatrix} w \\ q \end{bmatrix}$$

where δ_E and 'u' are the angle of deflection and control vector respectively, then the state equation for the above two equations can be written as:

$$\dot{x} = Ax + Bu \qquad (3)$$

where as:

$$A = \begin{bmatrix} Z_w & U_0 \\ (M_w + M_{\dot{w}} Z_w) & (M_q + U_0 M_{\dot{w}}) \end{bmatrix}, B = \begin{bmatrix} Z_{\delta_E} \\ M_{\delta_E} + Z_{\delta_E} M_{\dot{w}} \end{bmatrix}$$
$$\therefore [sI - A] = s\begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} - \begin{bmatrix} Z_w & U_0 \\ (M_w + M_{\dot{w}} Z_w) & (M_q + U_0 M_{\dot{w}}) \end{bmatrix}$$
$$= \begin{bmatrix} s & 0 \\ 0 & s \end{bmatrix} - \begin{bmatrix} Z_w & U_0 \\ (M_w + M_{\dot{w}} Z_w) & (M_q + U_0 M_{\dot{w}}) \end{bmatrix}$$
$$= \begin{bmatrix} s - Z_w & -U_0 \\ -(M_w + M_{\dot{w}} Z_w) & [s - (M_q + U_0 M_{\dot{w}})] \end{bmatrix}$$
$$\Delta_{sp}(s) = det[sI - A]$$
$$= s^2 + [-(Z_w + M_q + U_0 M_{\dot{w}})]s + [Z_w M_q - U_0 M_{\dot{w}}]$$
$$= s^2 + 2\zeta_{sp}\omega_{sp}s + \omega_{sp}^2 \qquad (4)$$

In (4):

$$2\zeta_{sp}\omega_{sp} = -(Z_w + M_q + U_0 M_{\dot{w}}),$$
$$\omega_{sp} = [Z_w M_q - U_0 M_{\dot{w}}]^{\frac{1}{2}} \qquad (5)$$

$$\frac{w(s)}{\delta_E(s)} = \frac{(U_0 M_{\delta_E} + M_q Z_{\delta_E})\left\{1 + \frac{Z_{\delta_E}}{U_0 M_{\delta_E} - M_q Z_{\delta_E}} s\right\}}{\Delta_{sp}(s)}$$

$$= \frac{K_w(1 + sT_1)}{\Delta_{sp}(s)}$$ where:

$$K_w = (U_0 M_{\delta_E} + M_q Z_{\delta_E}) \text{ and } T_1 = \frac{Z_{\delta_E}}{K_w}$$

Again, $\dot{\alpha} = \frac{\dot{w}}{U_0}$

$$\Rightarrow \alpha(s) = \frac{w(s)}{U_0}$$

$$\Rightarrow w(s) = U_0\alpha(s)$$

$$\Rightarrow \frac{\alpha(s)}{\delta_E(s)} = \frac{K_w(1+sT_1)}{U_0\Delta_{sp}(s)} \tag{6}$$

3.1. Stability derivatives of aircraft

The standard values of stability derivatives for CHARLIE aircraft in three different conditions are depicted in Table 1. These are intended for the aircraft's longitudinal dynamics. The transfer function for a specific flight condition can be found using stability derivatives.

Table 1. Stability derivatives of aircraft for three distinct flight conditions [31]

	Flight condition		
	FC-1	FC-2	FC-3
$U_0(ms^{-1})$	67	158	250
X_u	-0.021	0.003	-0.00002
X_w	0.122	0.078	0.026
X_{δ_E}	0.292	0.616	0.0
Z_W	-0.512	-0.433	-0.624
Z_q	-1.9	-1.95	-3.04
Z_{δ_E}	-1.96	-5.15	-8.05
M_W	-0.006	-0.006	-0.005
M_q	-0.357	-0.421	-0.668
M_{δ_E}	-0.378	-1.09	-2.08

3.2. Transfer functions of different flight conditions

Table 2 show the transfer function for FC-1, FC-2, and FC-3 respectevely. FC stands for flight condition. FC-1, FC-2, and FC-3 in Table 2 can be obtained by putting the parametric values from Table 1 in (6).

Table 2. Transfer functions for three different flight conditions

Flight conditions	G(S)
FC-1	$G_1(S) = \frac{0.04936S + 0.65835}{1.695S^2 + 2.1546S + 1}$
FC-2	$G_1(S) = \frac{0.0128S + 0.978}{0.8849S^2 + 1.59469S + 1}$
FC-3	$G_3(S) = \frac{0.0193S + 1.26}{0.599S^2 + 1.525S + 1}$

4. PROPOSED OPTIMIZATION SOFT COMPUTING TECHNIQUES

There are so many methods for determining the gain of PI controller. Among them GA and PSO methods are applied here for tuning the controller. Numerous optimization techniques have been used to address the different kinds of real-world issues in various sectors. The TLBO approach is thought to be superior to the rest among them.

4.1. Teaching learning-based optimization

Following its introduction by Rao *et al*. [32], TLBO has gained a lot of popularity in the engineering domain. Its stability analysis, time consumption, and solution quality are superior than those of other methods. In general, TLBO operates in two stages: In the first stage, known as the teacher phase, students learned from their individual teachers; in the second stage, known as the learner phase, students learn from one another through interaction. The following steps are part of the TLBO algorithm.

4.1.1. Initialization

The population size is taken as [NP D]. In this case NP indicates size of population i.e. number of learners and D indicates the dimension of the problem i.e. number of subjects offered. The *i*th column of the initial population represents the marks secured by different learners in *i*th subject.

Initial population= $\begin{matrix} x_{1,1} & x_{1,2} & \cdots & x_{1,D} \\ x_{2,1} & x_{2,2} & \cdots & x_{2,D} \\ . & . & . & . \\ . & . & . & . \\ x_{NP,1} & x_{NP,2} & \cdots\cdots & x_{NP,D} \end{matrix}$

4.1.2. Teacher phase

During this phase, the designated instructor puts up their best effort to raise the class mean. Since teachers are the ones who train the students, the best learner's solution always goes to that specific teacher. The average grades obtained by various pupils in various assignments are computed (7).

$$M_d = [m_1, m_2, \dots, m_D] \tag{7}$$

whereas m_1 is the aggregate marks secured by the students in ith paper. The dissimilarity in mean results of a particular teacher is represented as $M_{diff} = rand(0,1)[X_{best} - T_F M_d]$. In which rand $(0, 1)$ is chosen arbitrarily as 0 or 1 and T_F as teaching factor. T_F is taken arbitrarily either 1 or 2.

$$T_F = round[1 + rand(0,1)] \tag{8}$$

In (9) the exiting population is renewed as (9):

$$X_{new} = X + M_{diff} \tag{9}$$

X_{new} is accepted if $(X_{new}) < f(X)$, where $f(X)$ is taken as the objective function.

4.1.3. Learner phase

In this case, the teacher chooses a student at random through contact in order to advance their knowledge. If other pupils are more knowledgeable than him, then he can effectively learn more from them through interaction. The steps involved in learning stage are as follows. Randomly select two learners X_i and X_j such that i =/ j.

$$X_{new} = X_i + rand(0,1)(X_i - X_j). \qquad \text{If}(X_j) < f(X_j) \tag{10}$$

$X_{new} = X_i + rand(0,1)(X_j - X_i)$. Take X_{new} as granted if better performance is found.

5. SIMULATION RESULT

In this part, TLBO technique is used for designing the best variables of a PI system employing the transfer function of first flight condition. A comparison is made between TLBO with PI and conventional methods for comparing the advantages of proposed controllers. Step responses of the flight control system employing TLBO–PI, GA and PSO methods are obtained by varying three different parameters from -50% to +50% are shown from Figures 3 to 14. Similar figures can also be drawn by varying the remaining parameters. It is evident from these figures that settling time of the suggested TLBO approach is lower in comparison to PSO and GA procedures.

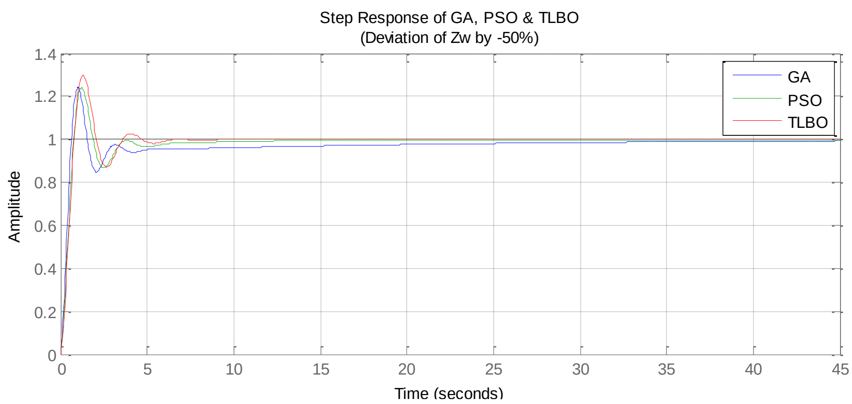

Figure 3. Deviation of Z_W by -50%

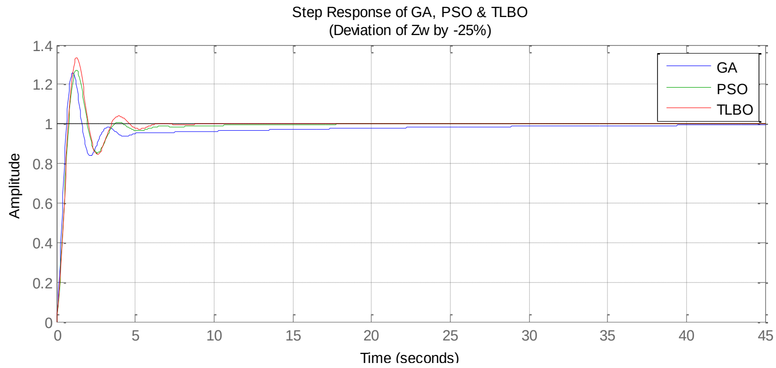

Figure 4. Deviation of Z_W by -25%

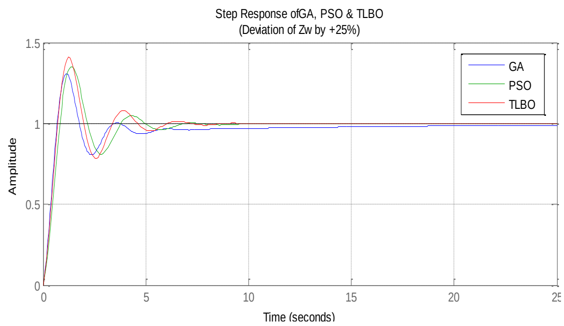

Figure 5**.** Deviation of Z_W by +25%

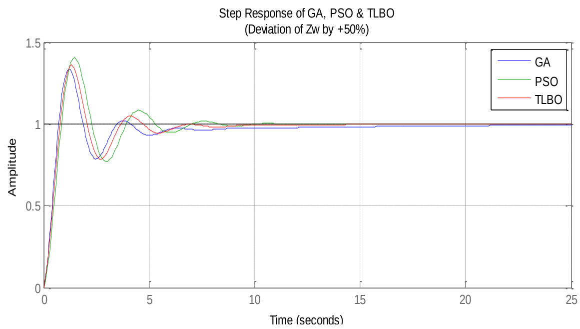

Figure 6. Deviation of Z_W by +50%

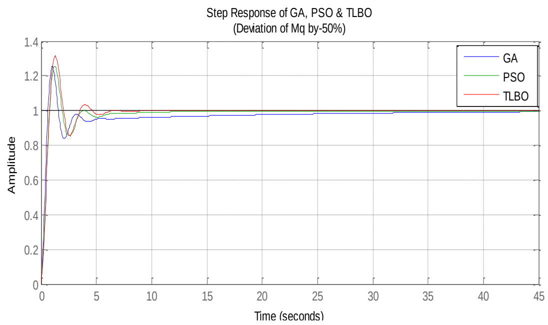

Figure 7. Deviation of Mq by-50%

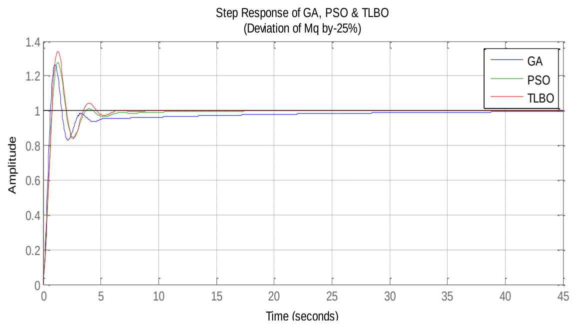

Figure 8. Deviation of Mq by-25%

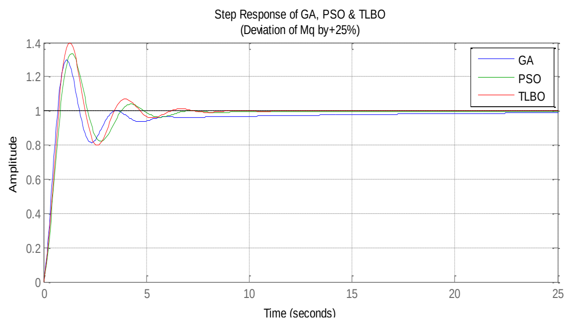

Figure 9. Deviation of Mq by+25%

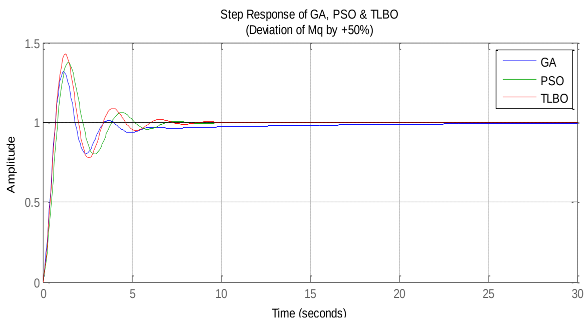

Figure 10. Deviations of Mq by+50%

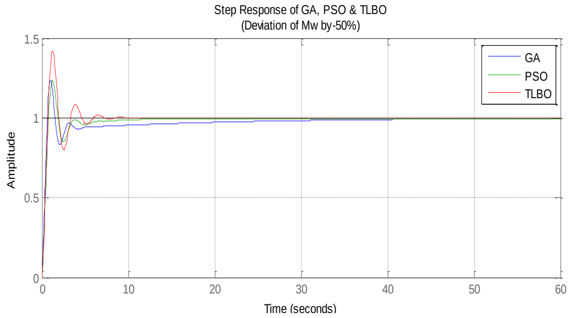

Figure 11. Deviation of Mw by -50%

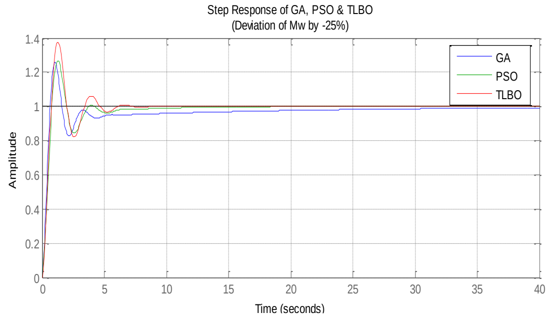

Figure 12. Deviation of Mw by -25%

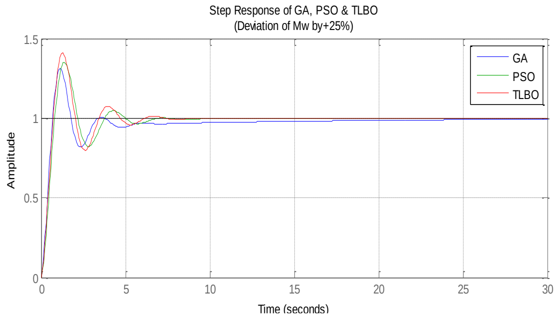

Figure 13. Deviation of Mw by +25%

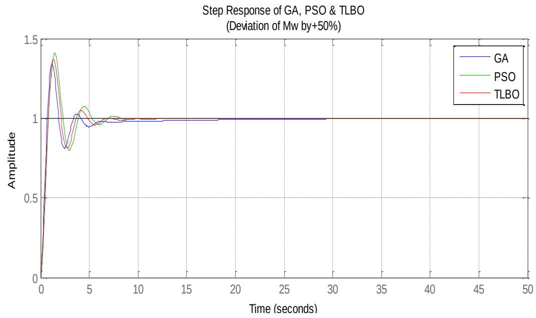

Figure 14. Deviation of Mw by +50%

6. ROBUSTNESS ANALYSIS

For testing the toughness of the CHARLIE Aircraft, the parameters are changed from-50% to +50%. Then robustness is measured by using the optimum values obtained from TLBO optimized PI controller. A comparison results among GA, PSO and TLBO are also depicted in Table 3 and 4 respectively. Different analysis results related to integral absolute error (IAE), integral time absolute error (ITAE), and mean square error (MSE), settling time, peak under-shoots and peak overshoots are given in these tables. Now it is obvious that the proposed technique is quite powerful when subjected to a large range of parametric variation. But also retuning of controller parameters does not necessary over the wide range. Similarly, the performance indices obtained from TLBO is less than that obtained from conventional methods like GA and PSO.

Table 3. Variation of settling time, under shoot, and over shoot, IAE, ITAE, and MSE for GA and TLBO

Deviation of parameters (%)	GA						TLBO					
	Ts	Ush	Osh	IAE	ITAE	MSE	Ts	Ush	Osh	IAE	ITAE	MSE
-50	8.27	30.86	12.4	1.1	2.56	0.5	3.9	75.47	35.4	0.7	0.7	0.3
-25	13.9	40.14	19.9	1.1	5	0.6	3.51	57.55	27.7	0.8	1	0.4
+25	21.6	74.62	36.8	1.5	6.5	0.7	6.8	79.93	40.5	1.3	2.5	0.5
+50	22.3	84	46.6	1.7	6.9	0.8	8.4	38.9	48.5	1.4	4	0.6

Table 4. Variation of settling time, under shoot, and over shoot, IAE, ITAE, and MSE for PSO and TLBO

Deviation of	PSO						TLBO					
parameters (%)	Ts	Ush	Osh	IAE	ITAE	MSE	Ts	Ush	Osh	IAE	ITAE	MSE
-50	5.56	61.8	29	1	1.3	0.4	3.9	75.47	35.4	0.7	0.7	0.3
-25	3.8	52.8	26.4	0.9	1.2	0.5	3.51	57.55	27.7	0.8	1	0.4
+25	8.4	76.61	37.6	1.4	2.7	0.6	6.8	79.93	40.5	1.3	2.5	0.5
+50	9.42	86	47.3	1.6	4.3	0.7	8.4	38.9	48.5	1.4	4	0.6

The above comparison values are also displayed in form of bar charts from Figures 15 to 18. Thus, the analysis shows better result for TLBO optimized PI controller than PSO and GA methods. In Table 5 to 7**,** variation of performance indices like ITAE, MSE, and IAE are demonstrated.

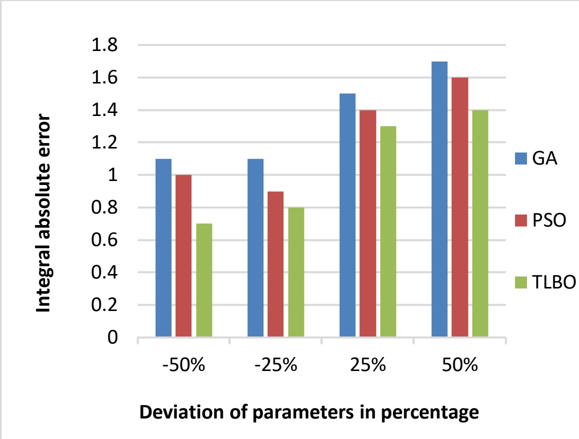

Figure 15. IAE among TLBO, PSO, and GA

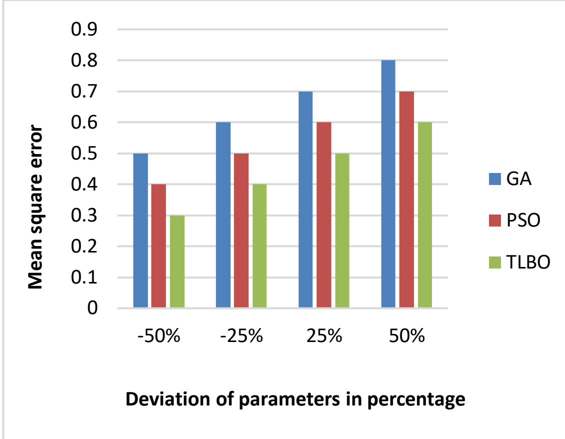

Figure 16. MSE among TLBO, PSO, and GA

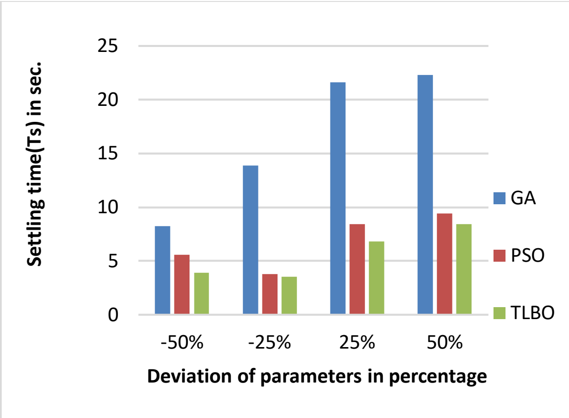

Figure 17. Ts among TLBO, PSO, and GA

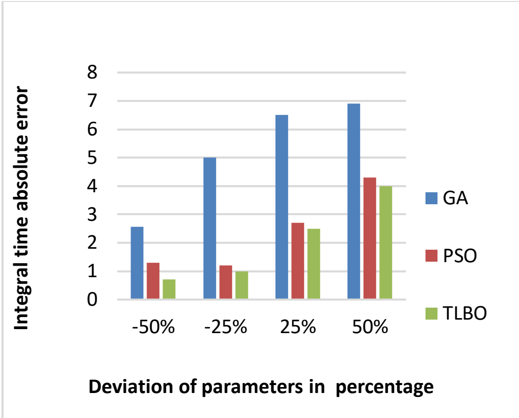

Figure 18. ITAE among TLBO, PSO, and GA

Table 5. Variation of IAE, ITAE, and MSE

Parameters	%Deviation	GA			PSO			TLBO		
		IAE	ITAE	MSE	IAE	ITAE	MSE	IAE	ITAE	MSE
Z_w	-50	1.23	7.04	0.29	0.88	2.16	0.34	0.83	1.04	0.27
	-25	1.22	6.6	0.31	0.89	1.85	0.36	0.88	1.18	0.30
	+25	1.23	5.56	0.36	1.05	1.82	0.44	1.04	1.68	0.33
	+50	1.24	4.98	0.39	1.24	2.45	0.51	1.11	2.40	0.37
M_q	-50	1.25	7.11	0.31	0.89	2.07	0.35	0.86	1.14	0.30
	-25	1.24	6.63	0.32	0.91	1.86	0.37	0.90	1.25	0.31
	+25	1.21	5.62	0.35	1.02	1.74	0.43	1.01	1.62	0.34
	+50	1.20	5.05	0.37	1.12	1.96	0.47	1.08	1.83	0.35
U_0	-50	1.01	1.86	0.44	2.12	7.18	0.83	0.82	1.04	0.34
	-25	1.11	4.08	0.37	1.13	1.92	0.49	0.99	1.53	0.36
	+25	1.27	7.29	0.41	0.97	2.82	0.35	0.44	1.37	0.32
	+50	1.26	7.82	0.28	1.40	4.18	0.32	1.05	3.04	0.37
M_w	-50	1.36	8.30	0.41	1.03	2.51	0.35	0.94	1.61	0.31
	-25	1.29	7.25	0.42	0.96	2.03	0.37	0.93	1.37	0.33
	+25	1.16	5.01	0.40	1.03	1.70	0.43	1.02	1.63	0.35
	+50	1.12	3.93	0.38	1.17	2.08	0.49	1.05	1.98	0.37
	-50	1.09	5.00	0.41	0.94	1.83	0.37	0.93	1.79	0.31
$M_{\delta E}$	-25	1.15	5.49	0.42	0.95	1.78	0.38	0.94	1.15	0.32
	+25	1.34	7.04	0.41	0.97	1.68	0.42	0.96	1.40	0.36
	+50	1.45	8.27	0.42	0.99	1.58	0.47	0.97	1.45	0.35
$Z_{\delta E}$	-50	1.15	4.73	0.37	1.03	1.55	0.46	0.82	1.08	0.36
	-25	1.20	5.48	0.38	0.96	1.46	0.43	0.88	1.22	0.35
	+25	1.21	6.36	0.36	1.17	2.51	0.37	0.99	2.07	0.32
	+50	1.13	5.77	0.37	1.08	3.72	0.34	1.06	2.47	0.33

Table 6. Variation of settling time, under shoot, and over shoot

Parameters	%Deviation	GA			PSO			TLBO		
		Ts	Ush	Osh	Ts	Ush	Osh	Ts	Ush	Osh
Z_w	-50	23.9	16.67	24	6.16	16.88	24	4.32	20.10	23.9
	-25	21.1	17.54	26	6	18.3	27	5.62	21.26	25.6
	+25	16	18.98	30.5	6.36	21.11	34.8	5.77	22.74	34.2
	+50	13.5	19.86	33.4	6.71	22.27	40.4	6.28	20.89	33.1
M_q	-50	23.5	17.23	25.2	6.07	17.73	25.6	5.58	20.67	25.1
	-25	20.9	17.61	26.6	6.04	18.19	27.8	5.69	21.48	26.2
	+25	16.4	18.93	29.8	6.29	20.48	33.6	5.84	22.88	29.6
	+50	14.1	19.18	31.7	6.52	21.72	37.2	5.82	23.17	31.5
U_0	-50	7.11	17.79	25.6	12.6	23.84	52	4.39	22.52	25.1
	-25	11.3	17.34	25.7	6.98	22.02	35.7	5.69	23.76	25.5
	+25	27	18.92	30.6	7.99	18.78	29.4	5.74	21.46	29.3
	+50	36.3	19.95	32.8	11.8	18.63	29.9	8.69	23.23	29.4
M_w	-50	27	15.97	23.5	8.03	16.1	23.3	5.66	23.47	23.2
	-25	22.8	17.05	25.7	6.15	17.78	26.6	5.66	22.36	25.5
	+25	14.4	19.43	31	6.28	21.38	35.2	5.82	23.29	30.9
	+50	10.4	20.98	34.2	6.57	23.49	40.8	6.22	21.81	33.8
	-50	15.4	21.6	37.2	5.18	21.99	37.9	5.1	21.76	37.1
$\mathrm{M}_{\delta\mathrm{E}}$	-25	17.1	20.4	33.3	5.56	20.9	34.6	5.25	17.1	20.4
	+25	19.9	14.93	21.4	6.75	17.47	25.4	6.33	20.02	21.3
	+50	20.8	9.02	11.7	5.04	14.2	18,7	4.81	15.56	11.6
$Z_{\delta E}$	-50	12.9	14.59	20.3	5.5	20.16	30.2	5.48	20.89	20.2
	-25	15.3	16.23	23.7	6.43	19.85	29.7	5.65	21.74	23.5
	+25	22.7	20.23	34.1	7.56	20.62	33.6	6.34	23.03	33.1
	+50	25.9	23.16	44	9.84	21.74	40.1	7.52	23.53	39.8

Table 7. Controller parameters for GA, PSO, and TLBO

Parameters	%Deviation	GA		PSO		TLBO	
		Kp	Ki	Kp	Ki	Kp	Ki
Z_w	-50	23.5	1.2	16.31	3.12	14.5	5.5
	-25	21.5	1.25	14.94	3.3	13.8	5.7
	+25	17.5	1.37	12.2	3.62	14.8	4.7
	+50	15.6	1.45	10.8	3.84	13.2	2.7
M_q	-50	22.3	1.2	15.5	3.2	14.6	5.2
	-25	20.9	1.25	14.5	3.3	13.5	4.5
	+25	18.2	1.35	12.6	3.6	12.9	5.6
	+50	16.8	1.42	11.7	3.74	14.8	4.7
U_0	-50	8.2	1.9	5.72	5.26	13.5	5.8
	-25	13.5	1.56	9.4	4.1	14.8	7.4
	+25	26.4	1.12	18.32	2.95	13.8	5.7
	+50	33.9	0.98	23.6	2.6	12.2	10.6
M_w	-50	22.6	1.21	15.7	3.2	15	10.8
	-25	21.1	1.25	14.65	3.3	14.6	7.4
	+25	18	1.35	12.5	3.6	13.9	5.8
	+50	16.5	1.42	11.43	3.74	13.2	2.72
	-50	19.5	1.06	13.6	2.8	13.6	2.74
$M_{\delta E}$	-25	19.5	1.16	13.6	3.06	0.82	0.01
	+25	19.5	1.5	13.6	3.96	13.9	5.4
	+50	19.5	1.8	13.6	4.9	14.5	5.6
$Z_{\delta E}$	-50	13	1.6	9.05	4.2	13.6	4.9
	-25	15.6	1.45	10.9	3.84	14.5	5.4
	+25	26	1.12	18.1	2.97	13.2	5.9
	+50	39.1	0.9	27.2	2.4	12.2	5.8

7. RESULT ANALYSIS

Using the Simulink platform in MATLAB 2014, the time domain simulated results of various reactions are achieved. With respect to this, the suggested flight control system model is created in the Simulink environment; however, the necessary programmes for the suggested GA, PSO, and TLBO approach are written in.m files. A step input is given for studying the behavior of a PI run flight system. Result obtained is compared with that of GA and PSO methods. It is obvious that the TLBO optimized PI managed device additionally offers higher dynamic response when subjected to a parametric change.

In Tables 3 and 4, deviation of performance indices like ITAE, MSE, and IAE are depicted along with settling time, undershoots, and overshoots. In each and every case it shows less error for IAE, ITAE, and MSE and less settling time also in TLBO optimized PI controller than that of GA and PSO. In addition to this, Tables 5 and 6 indicate the various analytical results of overshoots, settling time, undershoots, IAE, ITAE and

MSE corresponding to deviation of all parameters in four stages ranging from -50% to +50% at a stretch of 25%. These comparison values are also displayed in form of bar charts from Figures 15 to 18. Similarly, Table 7 shows the controller parameters for GA, PSO, and TLBO respectively.

Thus, the presented observations shows better result for TLBO optimized PI controller than the GA and PSO methods. Pictorial representation of overshoot, undershoot and settling time are also given from Figures 3 to 14 for verification. The above result indicates that the suggested TLBO algorithm gives better steady state output as compared to above two mentioned PI managed device.

8. CONCLUSION

To study the overall achievement of a flight control system, a PI controller is applied here along with TLBO algorithm for getting the best gain of PI controller. Then a comparison is made between GA, PSO and TLBO based PI controller for dynamic performance. A better result is achieved in TLBO managed PI controller than GA and PSO. For studying the behavior of the aircraft under various hazardous conditions, its controlling parameters are changed from -50% to +50% of nominal value in steps of 25%. Final results come in favor of TLBO and retuning of parameters is not necessary over a wide range.

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