Determination of Attacking Angle of Aircraft in Bio Inspired Optimized Technique

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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 GA and 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) etc. 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.

Key-Words: Proportional–Integral (PI), ParticleSwarmOptimization (PSO), TeachingLearningbased Optimization (TLBO), Genetic Algorithm (GA), Mean Square Error (MSE), Integral Absolute Error (IAE).

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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. [5] Different soft computing techniques like Fuzzy Model Reference Learning (FMRLC) 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 TLBO is incorporated in this paper mainly for adjusting the angle of attack as well as upgrading the overall achievement of the proposed system. [6-12]. Finally a comparison is made between the results of TLBO and conventional 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 PI controller for nonlinear second order plants was suggested by Rahul kumara, IdamakantiKasireddy, Abhishek Kumar, A K Singh. in an organized manner. [1] The regulating of a PI controller for a control system was verified by Zhenglong Xiang, Xiangjun Shao et all in a number of ways. [2] A better proposal was proposed by SahajSaxena, Yogesh V Hote, for determining the gain of a Proportional Integral controller. [3] Later an easy and quick method for tuning a PID controller was jointly analyzed by M. A. Abdel Ghany, M. E. Bahgat, W. M. Refaey, SolimanSharaf in a precise manner [4]. The various types of methods needed for estimating the angle of attack of a flight were clearly described by L.Sankaralingam, C.Ramprasadh in 2019. [5] Two-stage teaching-learning-based optimization method for flexible job-shop scheduling was suggested by R. Buddala and S. S. Mahapatrain 2019. [6] S. T. Suganthiet all proposed an improved teaching learning based optimization algorithm. [7]. A modified teaching–learning-based optimization algorithm for numerical function optimization was suggested by P. Niuet all. [8]M. Shahrouzi, F. Rafiee-Alavijeh and M. Aghabaglou suggested an hybrid bat algorithm and teaching–learning based optimization.[9] A novel TLBO with error correction for path planning of unmanned air vehicle was proposed by Z. Zhai, G. Jia and W. Kai. [10] Z. Zhang, H. Huang, C. Huang and B. Han suggested an improved TLBO with logarithmic spiral and triangular mutation for global optimization. [11] Nayak et al proposed an Elitist teaching–learning-based optimization (ETLBO) with higher-order Jordan Pi-sigma neural network. [12]. Yang et al. proposed a multiobjective genetic algorithm on an accelerator lattice [13]. In addition, Gaing proposed a particle swarm optimization method to solve the economic dispatch [14]. Evtushenko and Posypkin suggested a new method in 2013 for global box -constrained optimization [15]. Yassami M & Ashtari PA in 2013 proposed a novel hybrid optimization algorithm [16]. Storn R, Price K on 1997 proposed on. Diferential evolution for global optimization over continuous spaces [17]. In 2005, a fuzzy adaptive diferential evolution algorithm on soft computing was suggested by. Liu J, Lampinen J. A [18]. Dorigo M et al proposed on ant colony optimization in 2006 & 2008 respectevely [19 20]. Placement of wind turbines using genetic algorithms was suggested by Grady SA, Hussaini MY, Abdullah MMin 2005[21]. On 2009, GPU-based parallel particle swarm optimization was proposed by Zhou Y & Tan Y. [22]. A survey on new generation metaheuristic algorithms was jontly suggested in 2019 by Dokeroglu T, Sevinc E, Kucukyilmaz T & Cosar A [23]. Hussain K, Salleh MNM, Cheng S, Shi Y. done a comprehensive survey on Artificial Intell Rev.in 2019[24]. Various works on Particle Swarm Optimization using different techniques ware proposed by Fang H, Zhou J et al [25 28]. PSO-based memetic algorithm for flow shop scheduling was suggested by. Liu B, Wang L, Jin YH. in 2007[29]. Yang J, He L & Fu in 2014 suggested an improved PSO-based charging strategy of electric vehicles in electrical distribution grid [30].

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 and conventional methods, it was found that TLBO performs better in all aspects than GA and PSO methods for tuning the PI controller.

2. Block Diagram for determining the Angle of Attack

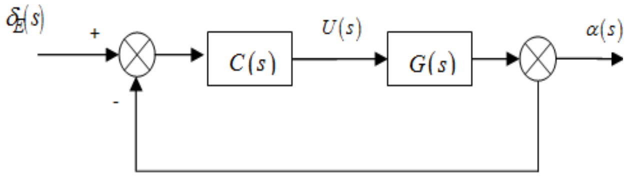

Fig.1: (Schematic diagram of angle of attack for an aircraft system.)

Where $\delta_E(s)$= the deflection angle of elevator.
α = angle of attack of the aircraft
G(s) = the forward path gain
C(s) = 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 below.

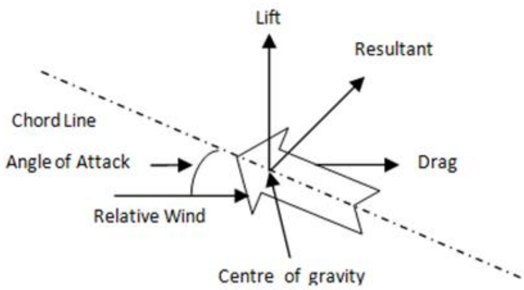

Fig.2: (Description of angle of attack)

Aircraft speed (u), is changed due to the deflection in control surfaces and atmospheric turbulence etc. 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:

$$\dot{w} = Z_w w + U_0 q + Z_{\delta_s} \delta_E \qquad (1)$$

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

$$= \left(M_{\dot{w}} + M_w Z_w\right) w + \left(M_q + U_0 M_w\right) q + \left(M_{\delta_z} M_{\dot{w}}\right) \delta_E$$

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

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

$$A = \begin{bmatrix} Z_w & U_0 \\ \left(M_w + M_{\dot{w}} Z_w\right) & \left(M_q + U_0 M_{\dot{w}}\right) \end{bmatrix},$$

$$B = \begin{bmatrix} Z_{\delta_E} \\ M_{\delta_E} + Z_{\delta_E} M_{\dot{w}} \end{bmatrix}$$

$$\therefore [sI - A] =$$

$$s\begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} - \begin{bmatrix} Z_w & U_0 \\ \left(M_w + M_{\dot{w}} Z_w\right) & \left(M_q + U_0 M_{\dot{w}}\right) \end{bmatrix}$$

$$= \begin{bmatrix} s & 0 \\ 0 & s \end{bmatrix} - \begin{bmatrix} Z_w & U_0 \\ \left(M_w + M_{\dot{w}} Z_w\right) & \left(M_q + U_0 M_{\dot{w}}\right) \end{bmatrix}$$

$$= \begin{bmatrix} s - Z_w & -U_0 \\ -\left(M_w + M_{\dot{w}} Z_w\right) & \left[s - \left(M_q + U_0 M_{\dot{w}}\right)\right] \end{bmatrix}$$

$$\Delta_{sp}(s) = \det[sI - A]$$

$$= s^2 + \left[-\left(Z_w + M_q + U_0 M_{\dot{w}}\right)\right] s + \left[Z_w M_q - U_0 M_{\dot{w}}\right]$$

$$= s^2 + 2\zeta_{sp}\omega_{sp} s + \omega_{sp}^2 \quad (4)$$

In equation (4)

$$2\zeta_{sp}\omega_{sp} = -\left(Z_w + M_q + U_0 M_{\dot{w}}\right),$$

$$\omega_{sp} = \left[Z_w M_q - U_0 M_{\dot{w}}\right]^{\frac{1}{2}} \quad (5)$$

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

$$= \frac{K_w\left(1 + sT_1\right)}{\Delta_{sp}(s)}$$ Where

$K_w = \left(U_0 M_{\delta_E} + M_q Z_{\delta_E}\right)$ And $T_1 = \dfrac{Z_{\delta_E}}{K_w}$

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

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

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

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

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

3.1 Stability Derivatives of Aircraft (CHARLIE)

The standard values of stability derivatives for CHARLIE aircraft in three different situations are depicted below.

Table 1

	Flight Condition(FC)		
	FC-1	FC-2	FC-3
$U_0\left(ms^{-1}\right)$	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

Source: Donald Mc Lean (1990)

3.2 Transfer Functions of different Flight Conditions

Transfer functions corresponding to three different flight conditions can be obtained after putting the above parametric values in equation (6) respectively are shown below in table-2.

Table 2

Flight Conditions(FC)	G(S) (Transfer Functions)
FC-1	$G_1(S)=\dfrac{0.04936S+0.65835}{1.695S^2+2.1546S+1}$
FC-2	$G_2(S)=\dfrac{0.0128S+0.978}{0.8849S^2+1.59469S+1}$
FC-3	$G_3(S)=\dfrac{0.0193S+1.26}{0.599S^2+1.525S+1}$

4. Conventional Methods

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.

5. Proposed Optimization Soft Computing Techniques

To tackle the various types of practical problems in different fields, a number of optimization methods have been applied. Among them TLBO method is considered as better than others.

5.1 TLBO (Teaching Learning Based Optimization)

After the application of TLBO in engineering fields it has become very popular after its initiation by Rao et al. Its quality of solution, time consumption and stability analysis is better than others. Generally, TLBO performs in two different phases: In the preliminary phase, learner acquired knowledge through their respective teachers known as teacher phase but in second stage learner learns among themselves by way of interactivity is generally called as learner phase. TLBO algorithm includes the following steps.

5.2 Initialization

Initially the size of population [NP D] is taken arbitrarily during this step, where NP shows the population strength and D shows the number of subjects offered. The different marks scored by students in the i^{th} subjects are shown in corresponding i^{th} column respectively.

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

5.3 Teacher Phase

In this phase maximum effort is given by the assigned teacher for improving the mean result of the class. Since the learners are trained through the teachers, the solution X_{best} for best learned person automatically goes to that particular teacher. The mean marks scored by different students in different papers are calculated below.

$$M_d=[m_1,m_2,\ldots\ldots,m_D] \quad (7)$$

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.

$$T_F=round[1+rand(0,1)] \quad (8)$$

In equation (9) below, the exiting population is renewed as

$$X_{new}=X+M_{diff} \quad (9)$$

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

5.4 Learner phase

Here, for improving the knowledge of a student a selection is made by the teacher randomly through interaction. A student can able in enhancing his knowledge successfully than other students through interaction if the others are better than him. The learning procedure is given below.

X_i And X_j are the two randomly preferred learners in which $i \neq j$

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

(10)

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

6. 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 Figure 3-14 below. 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 Particle Swarm Optimization (PSO) and Genetic Algorithm (GA) procedures.

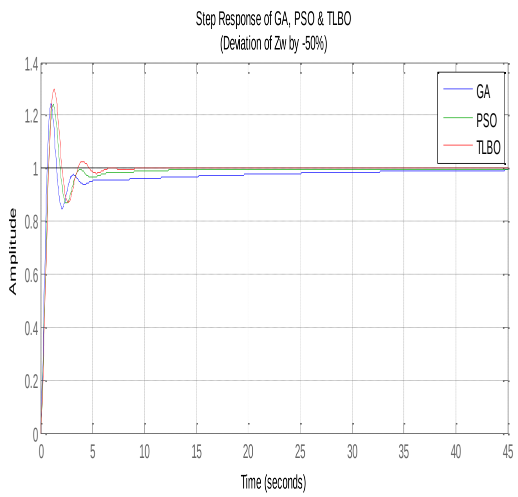

Fig. **3:** Deviation of Z_W by -50%

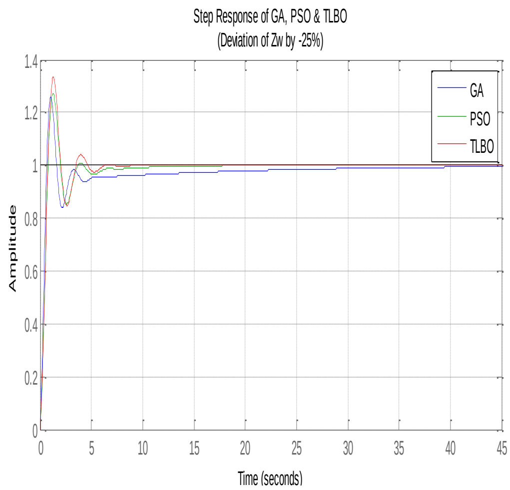

Fig.4: Deviation of Z_W by -25%

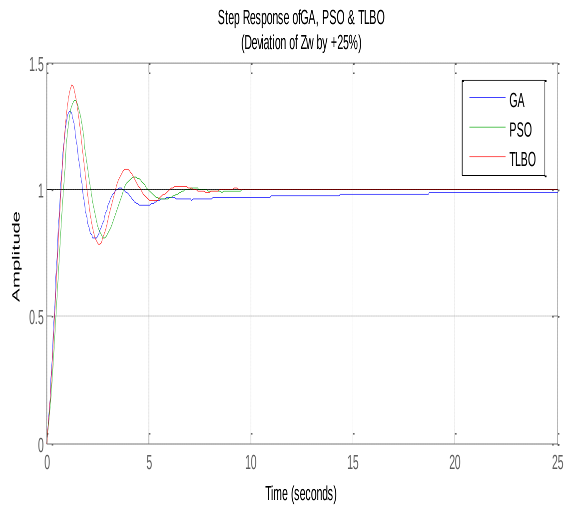

Fig.5: Deviation of Z_W by +25%

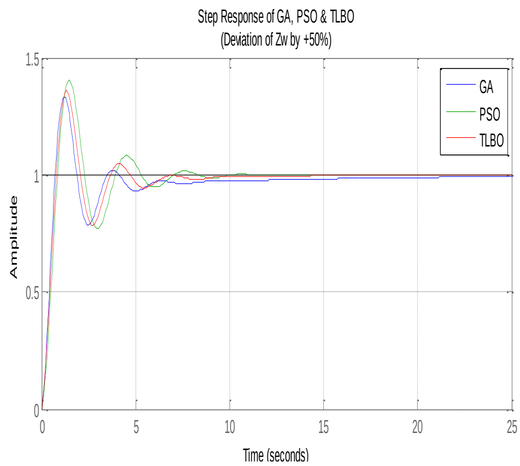

Fig.6: Deviation of Z_W by +50%

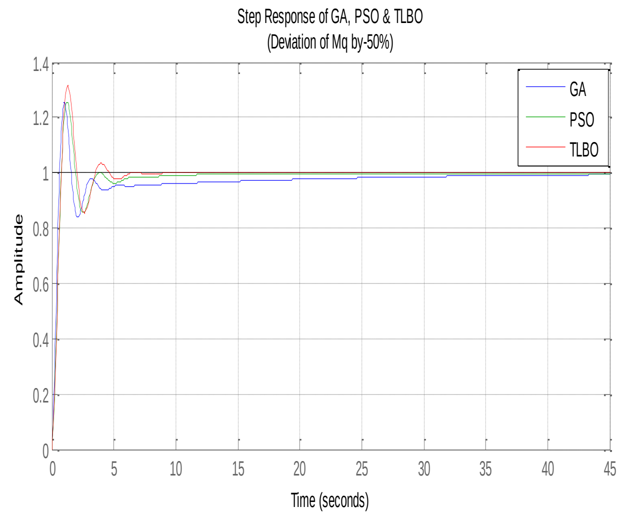

Fig.7: Deviation of M_q by -50%

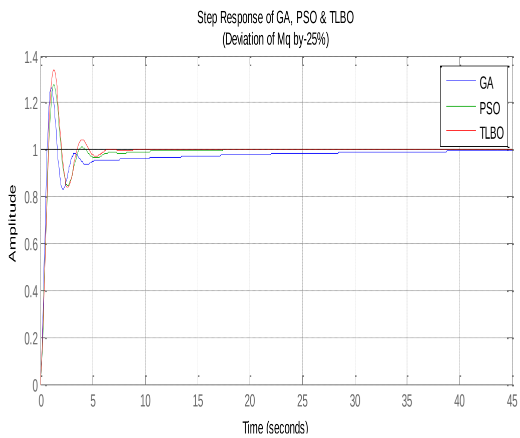

Fig.8: Deviation of M_q by -25%

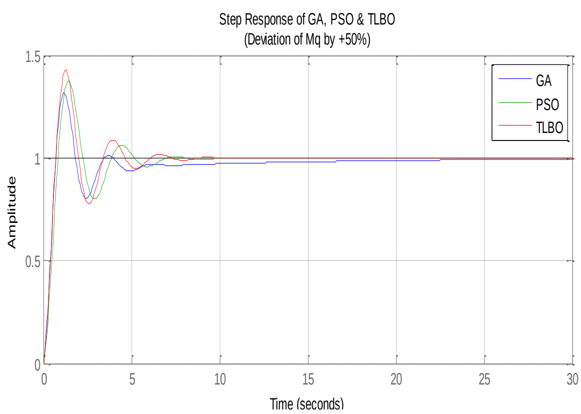

Fig.9: Deviation of M_q by +25%

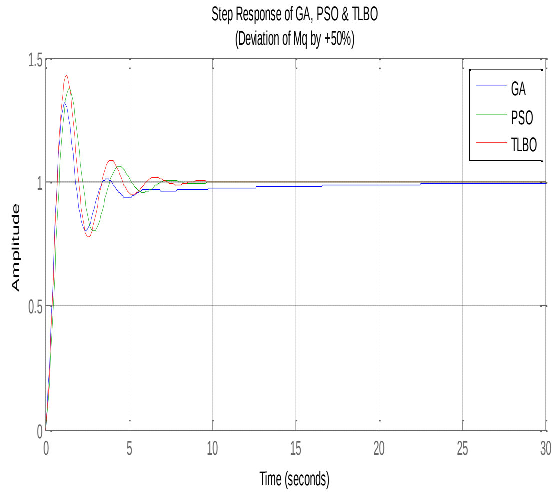

Fig.10: Deviation of M_q by +50%

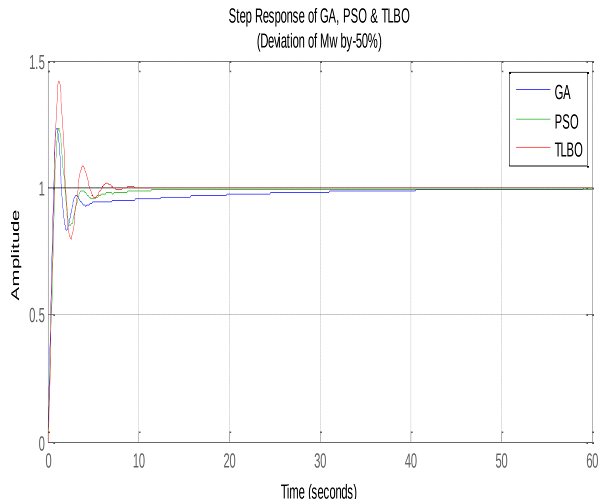

Fig. 11: Deviation of M_W by-50%

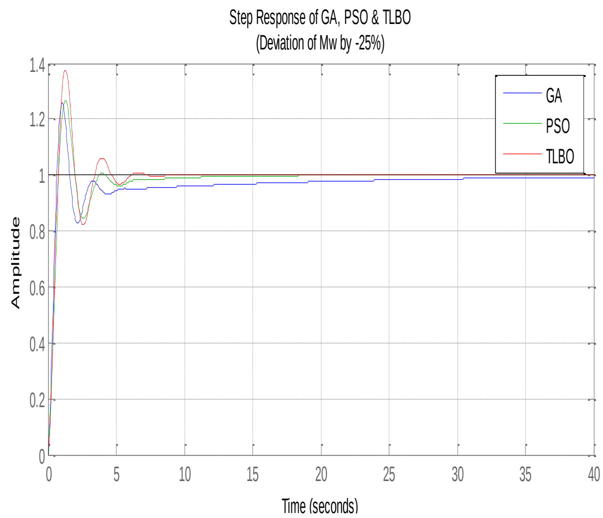

Fig.12: Deviation of M_W by-25%

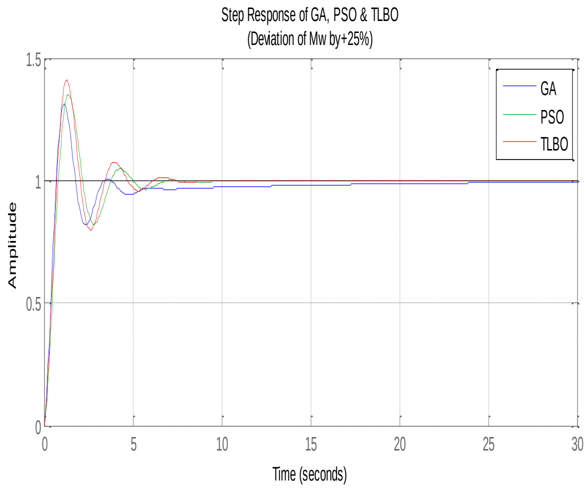

Fig.13: Deviation of M_W by+25%

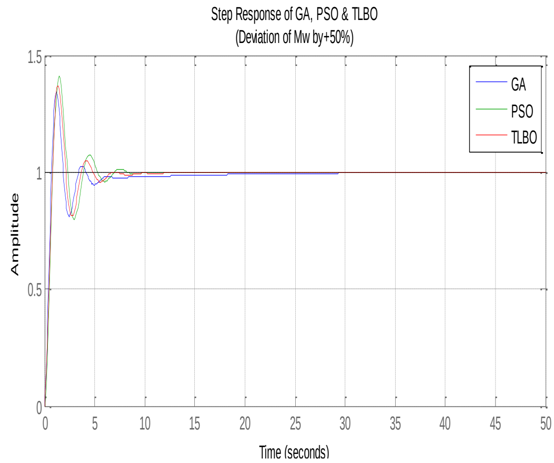

Fig.14: Deviation of M_W by+50%

7. 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 IAE, ITAE, and 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

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

Deviation of parameters	PSO						TLBO					
	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 figs.15-18. Thus, the analysis shows better result for TLBO optimized PI controller than PSO and GA methods.

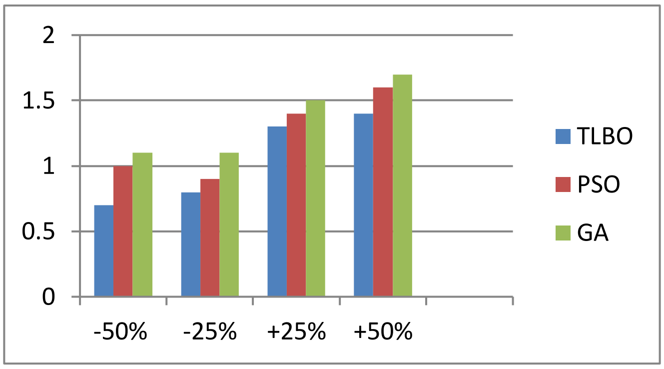

Fig.15: IAE among TLBO, PSO & **GA**

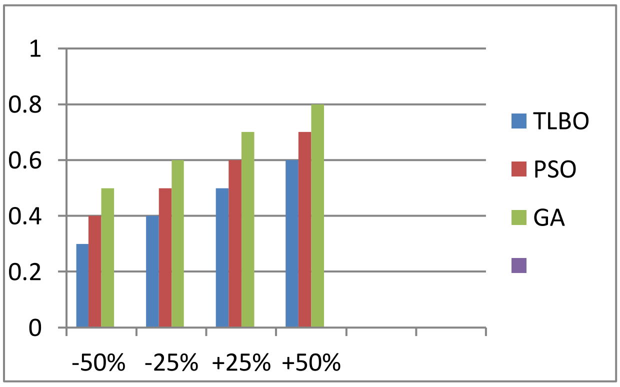

Fig.17: MSE among TLBO, PSO & GA

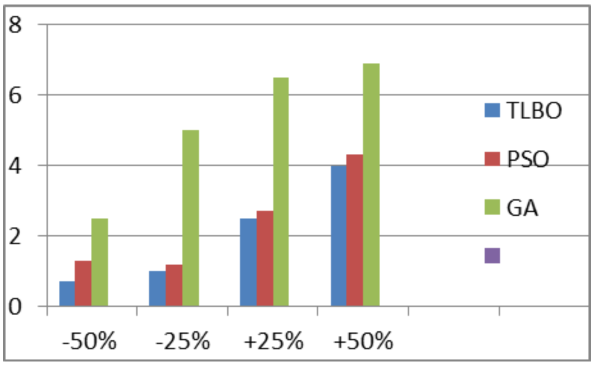

Fig16: ITAE among TLBO, PSO & GA

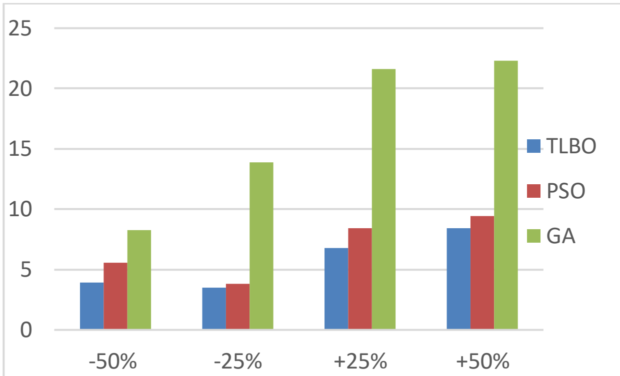

Fig: 18: Ts among TLBO, PSO & GA

In Table -5, variation of performance indices like Integral Time Absolute Error (ITAE), mean square error (MSE), Integral Absolute Error (IAE) etc. are demonstrated.

Table 5

Parameters	% Deviation	GA			PSO			TLBO		
		IAE	ITAE	MSE	IAE	ITAE	MSE	IAE	ITAE	MSE
	-50	1.23	7.04	0.29	0.88	2.16	0.34	0.83	1.04	0.27
Z_w	-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
$M_{\delta E}$	-50	1.09	5.00	0.41	0.94	1.83	0.37	0.93	1.79	0.31
	-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
	-50	1.15	4.73	0.37	1.03	1.55	0.46	0.82	1.08	0.36
$Z_{\delta E}$	-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

Parameters	%Deviation	GA			PSO			TLBO		
		Ts	Ush	Osh	Ts	Ush	Osh	Ts	Ush	Osh
	-50	23.9	16,67	24	6.16	16.88	24	4.32	20.10	29.9
Z_w	-25	21.1	17.54	26	6	18.3	27	5.62	21.26	33.6
	+25	16	18.98	30.5	6.36	21.11	34.8	5.77	22.74	40.8
	+50	13.5	19.86	33.4	6.71	22.27	40.4	6.28	20.89	36.1
	-50	23.5	17.23	25.2	6.07	17.73	25.6	5.58	20.67	31.7
	-25	20.9	17.61	26.6	6.04	18.19	27.8	5.69	21.48	34.2
M_q	+25	16.4	18.93	29.8	6.29	20.48	33.6	5.84	22.88	39.8
	+50	14.1	19.18	31.7	6.52	21.72	37.2	5.82	23.17	42.7
	-50	7.11	17.79	25.6	12.6	23.84	52	4.39	22.52	35.1
U_0	-25	11.3	17.34	25.7	6.98	22.02	35.7	5.69	23.76	41.7
	+25	27	18.92	30.6	7.99	18.78	29.4	5.74	21.46	35.3
	+50	36.3	19.95	32.8	11.8	18.63	29.9	8.69	23.23	48.4
	-50	27	15.97	23.5	8.03	16.1	23.3	5.66	23.47	41.5
M_w	-25	22.8	17.05	25.7	6.15	17.78	26.6	5.66	22.36	37.5
	+25	14.4	19.43	31	6.28	21.38	35.2	5.82	23.29	40.9
	+50	10.4	20.98	34.2	6.57	23.49	40.8	6.22	21.81	36.8
	-50	15.4	21.6	37.2	5.18	21.99	37.9	5.1	21.76	37.5
$M_{\delta E}$	-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	30.3
	+50	20.8	9.02	11.7	5.04	14.2	18,7	4.81	15.56	20.8
	-50	12.9	14.59	20.3	5.5	20.16	30.2	5.48	20.89	32
	-25	15.3	16.23	23.7	6.43	19.85	29.7	5.65	21.74	34.2
$Z_{\delta E}$	+25	22.7	20.23	34.1	7.56	20.62	33.6	6.34	23.03	41.1
	+50	25.9	23.16	44	9.84	21.74	40.1	7.52	23.53	44

8. Result Analysis

A step input is given for studying the behavior of a PI run flight system. Result obtained is compared with that of Genetic Algorithm (GA) and Particle Swarm Optimization (PSO) methods. It is obvious that the TLBO optimized PI managed device additionally offers higher dynamic response when subjected to a parametric change.

In Table-3 & 4, deviation of performance indices like ITAE (Integral Time Absolute Error), MSE (Mean Square Error), IAE (Integral Absolute Error) etc. are depicted along with settling time, undershoots and overshoots. In each and every case it **s**hows less error for IAE, ITAE and MSE and less settling time also in TLBO optimized PI controller than that of Genetic Algorithm (GA) and Particle Swarm Optimization (PSO). In addition to this, Table-5 and Table-6 indicate the various analytical results of IAE, ITAE, MSE, settling time, undershoots and overshoots 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 figs.15-18. Thus, the above analysis 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 figure 3-14 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.

9. 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 behaviour 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 favour of TLBO and retuning of parameters is not necessary over a wide range.

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