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Dynamic Stability Enhancement Using Fuzzy PID Control Technology for Power System

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Abstract: This article presents Fuzzy Particle Swarm Optimization of PID controller PSO-FPIDC used as a Conventional Power System Stabilizer CPSS to improve the dynamic stability performance of generating unit during low frequency oscillations. Speed deviation $\Delta\omega$ and acceleration $\Delta\dot{\omega}$ of synchronous generator are taken as input to the PSO-FPIDC controller connected to Single Machine Infinite Busbar SMIB system. This controller examined under different perturbation scenarios. The dynamic performance of the PSO-FPIDC is compared with the Fuzzy Teacher Learner Based Optimization PID TLBO-FPIDC, PSO-PID, TLBO-PID and optimal parameters of convectional Power System Stabilizer CPSS. The results show that the performance of PSO-FPIDC has small overshoot/undershoot and damp out lower frequency oscillations very quickly as compared to other controllers.

Keywords: Dynamic stability, fuzzy PID control, power system stabilizer, PSO, single machine infinite bus, TLBO.

1. INTRODUCTION

Stability of the synchronous generator in electrical power system will lost by an aperiodic deviation of rotor angle, or due to speed deviation oscillatory. This oscillations may sustain and grow due to insufficiency of damping torque. Power System Stabilizers PSS are present a damping torque for the purpose of reducing these oscillations caused by external perturbations by supply signal to excitation system and/or the speed governor system of the generating unit. The optimization techniques for tuning parameters of these devices in [1–4]. Most types of PSS utilize the classical linear control theory based on a linear model which has constant-parameters. Low-frequency oscillations are a wide spread problem in power systems at the same time power system are nonlinear and it is parameters changes with time [5–7]. Because PSS introduce complexity by introducing new states to the system. Therefore we use Proportional Integral Derivative PID controller optimized by intelligent techniques such as TLBO and PSO. For real time fast response fuzzy logic technique is applied in this work PSO-FPIDC.

Proportional integral derivative PID controllers are being popularly used by the industries for their simplicity and robustness. Through the growth of control theorems and technologies, today's conventional PID control technology has been perfectly overripe, it has unpretentious algorithm, obvious installation, comfortable setting, affluent expertise in application and other features [8, 9]. The parameters of this controller are fixed, can not be real-time compromised. Due to this various evolutionary and swarm intelligence based tuning methods have been proposed in literature [10–12]. The TLBO is applied for optimizing various engineering problems [13–15].

Fuzzy Logic Control FLC has arise as a powerful tool and it start to be implement in various power system applications. The application of fuzzy logic control technique become clear to be most suitable one whenever a well-defined control objective cannot identify clearly, the system to be controlled is a complex, or its exact mathematical model is not obtained [16, 17]. FLC has a fixed set of control rules, usually derived from experts knowledge. The Membership Functions MFs of the associated input and output linguistic variables are generally predefined on a common universe of discourse. The investigation of adaptive fuzzy optimal control/filtering problems introduced in [18–26].

In this paper presents Particle Swarm Optimization Fuzzy PID controller PSO-FPIDC instead of Conventional Power System Stabilizer CPSS in Single Machine Infinite Busbar System SMIB, where the parameter of PID controller optimized by particle swarm optimization and Fuzzy logic Controller. Speed change $\Delta\omega$ and acceleration $\Delta\dot{\omega}$ of the rotor were taken as input to PSO-FPIDC controller to improve the dynamic stability performance of SMIB system, the system examined under different perturbations. The performance of the PSO-FPIDC is compared with the Fuzzy Teacher Learner Based Optimization

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TLBO-FPIDC, PSO-PID, TLBO-PID and optimal parameters of convectional Power System Stabilizer CPSS. The result shows that the performance of PSO-FPIDC has small overshoot/undershoot and damp out oscillations quickly as compared to other controllers.

2. PROBLEM PRESENTATION

Electric power systems configurations are quite nonlinear and over sensitive to be coming unstable if any sudden change occurred in the system operation. Power systems parameters are change with time. However the parameters of PSS will not change in real time. Accordingly PSO-FPIDC as power system stabilizer is used in this work. The Single Machine Infinite Busar SMIB with transmission-circuit reactance Fig. 1. In order to achieve the stability enhancement, speed change $\Delta\omega$ and acceleration $\Delta\dot{\omega}$ of SMIB is considered as input to PSO-FPIDC controller as presented in Fig. 2. The linear model of SMIB mostly used to study the performance of dynamic stability of electrical power system which contains the relationship of electromechanical torque between angle and speed changes of generating unit [27], Automatic Voltage Regulator AVR [6], high gain IEEE type ST1A model of the static excitation system is considered and transmission-circuit reactance is presented by a two axis, fourth order model is shown in Fig. 2 [6]. The PSO-FPIDC structure connected with rotor speed change as input has made a very nice contribution to improve system dynamic stability. where $\Delta\omega_r$, $\Delta\delta$ and $\Delta\psi_{fd}$ are speed change, rotor angle change and field flux change respectively. ΔE_{fd}, ΔT_e and ΔT_m represent field voltage change, electrical torque change and mechanical torque change respectively. ΔV_S, ΔV_1, V_{ref} and ΔE_t represent voltage transducer change, reference voltage change and terminal voltage change respectively. $G_{ex(s)} = K_A$, is the transfer function of exciter. Finally, K_A, K_1, ..., K_6, H, K_D, T_3 and T_R are parameters of system [6], they are functions of active power P with the exception of H.

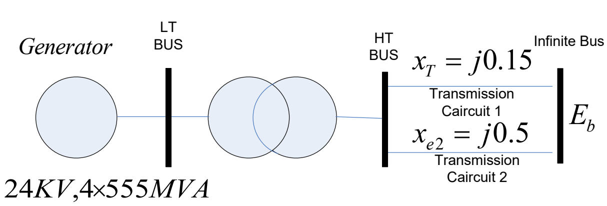

Fig. 1. Classical SMIB test system.

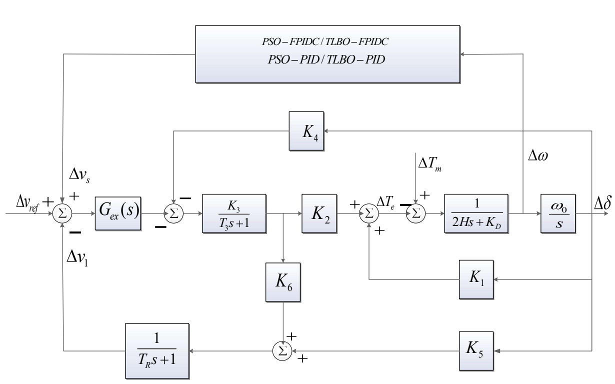

Fig. 2. SMIB model with CPSS/PSO-PID/PSO-FPIDC.

3. PSO OPERATION PRINCIPAL

Particle Swarm Optimization (PSO) algorithm is the optimization technique developed by Dr. Kennedy and Dr. Eberhart [28]. It is a multi-swarms search for best solution of object function and updating swarm values. In the Dimension-axis study of search area [29], the i^{th} swarms position represented by $X_i = (X_{i1}, ..., X_{im})$. The i^{th} swarm velocity of Dimension vector represented by $V_i = (V_{i1}, ..., V_{im})$. The best position given by the i^{th} particle is calculated as $P_i = (P_{i1} ..., P_{im})$ and P_G is position index of the particle found in the swarm previous position, then P_G become to be the global best position calculated, the particle velocity and new position will be calculated by using the following equations:

$$V_{im} = WV_{im} + C_1 r(P_{im} - X_{im}) + C_2 R(P_{gm} - X_{im}), \quad (1)$$

$$X_{im} = X_{im} + V_{im}, \quad (2)$$

where C_1 and C_2 are Personal and social Acceleration factors positive constants, and r is random values in interval [0,l]. The parameter W is the Inertia factor that increases the overall performance of PSO.

4. PID CONTROLLER TUNING USING (PSO)

The optimization problem is to optimize the PID controller and calculate the minimum value of object function. The object function would minimize steady state error E_{SS}, over-shoot M_p, rise-time t_r and settling-time t_s as presented in following (3) [30]:

$$F = (M_p + E_{ss})(1 - e^{-1.5}) + (t_s - t_r)e^{-1.5}. \quad (3)$$

Step 1: Define the parameters of PSO algorithms: number of iterations, swarm size, acceleration factors, inertia factor, the position matrix P_i and the velocity matrix V_i and constraints of K_P, K_I and K_D.

Step 2: Initialize value of each particle.

Step 3:: Compare between new and old fitness particle's personal position, after that update the personal best position's which called P_{best}.

Step 4: Continue Search for best P_{best} through all particles. And denote the best position as G_{best}.

Step 5: Update the V_i in (1), and P_i in (2).

Step 6: Update PID controller parameters.

Step 7: If reach the maximum iterations, then stop. The latest G_{best} is the optimal PID controller parameter. Otherwise, go to Step 2.

5. TLBO OPERATION

The teacher learner based optimization TLBO is proposed by Rao [31]. It has two phases, first one is teacher phase where teacher tries to improve the learners to his level. the second one is learner phase where learners interacts to improve their performance.

5.1. Teaching phase

Consider $X_t^i (i = 1,2,...m)$ is the i^{th} learner in the population, X_t^{best} is the best learner in the current iteration L. The $Mean_{t,j}$ is the value of mean result of learners in a particular subject j$(j = 1,2,...,n)$, T_F is the teaching factor and r_t is the random number which can be any value between 1 or 2. In a problem with n dimension, at any iteration t, we have the following notations as given in [32]:

Step 1: First compute the difference $D_{t,j}$ between the teacher (best learner) by taking random number r_t in the range [0,1]:

$$D_{t,j} = r_t(X_{t,j}^{best} - T_F Mean_{t,j}). \tag{4}$$

Step 2: Learner X_t^i update its state in subject j by combining the difference $D_{t,j}$ and its current state:

$$X_{t,j}^{i'} = X_{t,j}^i + D_{t,j}. \tag{5}$$

Step 3: If X_t^i, is better then replace the latter by the new value.

5.2. Learning phase

Step 1: For the learner X_t^i, randomly choose another learner X_t^k, if X_t^i is better than X_t^k, then:

$$X_t^{i'} = X_t^i + r_i(X_t^i - X_t^k). \tag{6}$$

Step 2: If X_t^k is better than X_t^i, then let:

$$X_t^{i'} = X_t^i + r_i(X_t^k - X_t^i). \tag{7}$$

Step 3: If $X_t^{i'}$ is better than X_t^i, then replace the better by the new value.

6. PID CONTROLLER TUNING USING TLBO

The steps of the proposed TLBO algorithm as follows:

Step 1: Define the lower and upper bounds of K_P, K_I and K_D, number of iteration, population size (learners).

Step 2: Choose the best learner X_t^{best} as a teacher.

Step 3: Evaluate the difference $D_{t,j}$ in (4).

Step 4: : Update learners by teacher knowledge (5).

Step 5: Update learners by other learner knowledge (6)-(9).

Step 6: Stop if a stopping criteria is achieved, else go to Step 3.

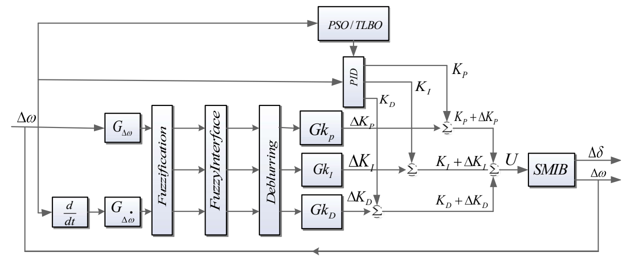

Fig. 3. Fuzzy PID Control System Structure connected to SMIB.

7. ADAPTIVE FUZZY-PID CONTROLLER PRINCIPLE

The fuzzy PID controller optimized by intelligent techniques is robust way to obtain real time fast dynamic response when sudden operating condition change occurred in power system. The PSO-FPIDC/TLBO-FPIDC controller is shown in Fig. 3. fuzzy controller has two inputs speed change $\Delta\omega$ and acceleration $\Delta\dot{\omega}$ of SMIB, through fuzzification, fuzzy inference and deblurring the controller output is adapted. The parameters $G_{\Delta\omega}$ and $G_{\Delta\dot{\omega}}$ are scale value to drive $\Delta\omega$ and $\Delta\dot{\omega}$ into the fuzzy domain, where GK_P, GK_I, GK_D are the scale values calculated by fuzzy to drive control quantity into the domain of the control object as factors of K_u. The domain of $\Delta\omega$, are respectively $[-\Delta\omega_{\max}, \Delta\omega_{\max}]$ and $[-\Delta\dot{\omega}_{\max}, \Delta\dot{\omega}_{\max}]$, The domain of the output is $[-u_{\max}, u_{\max}]$. In (8) n and m are the maximum output values of fuzzy domain, l_1, l_2, l_3 is the large calculated fuzzy value for K_u.

$$G_{\Delta\omega} = \frac{n}{\Delta\omega_{\max}},\quad G_{\Delta\dot{\omega}} = \frac{m}{\Delta\dot{\omega}_{\max}},\quad GK_P = \frac{u_{\max}}{l_1},$$
$$GK_I = \frac{u_{\max}}{l_2},\quad GK_D = \frac{u_{\max}}{l_3}. \tag{8}$$

8. DETERMINE OF MEMBERSHIP DEGREE

In the conventional (PID) controller formula [33] is:

$$U(t) = K_P e(t) + K_I \int_0^t e(t)dt + K_D \frac{de(t)}{dt}. \tag{9}$$

After PSO-PID parameter optimized by fuzzy controller, the parameters into real time variable, so the control can be written as:

$$U(t) = (K_P + \Delta K_P)e(t) + (K_I + \Delta K_I) \int_0^t e(t)dt$$
$$+ (K_D + \Delta K_D)\frac{de(t)}{dt}. \tag{10}$$

In (9) and (10) $e(t) = \Delta\omega$, ΔK_P, ΔK_I, ΔK_D is $(K_u \times GK_u)$ type the membership of each state determined, this ac-

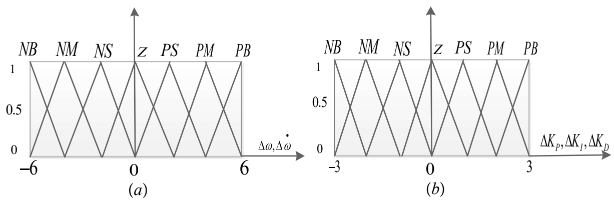

Fig. 4. Membership functions of (a) $\Delta\omega$, $\Delta\dot{\omega}$. (b) Membership function of ΔK_P, ΔK_I, ΔK_D.

cording to experiment personal experience. Here the domain $\Delta\omega$ and $\Delta\dot{\omega}$ is $[-6,-4,-2,0,+2,+4,+6]$, the domain of output is $[-3,-2,-1,0,+1,+2,+3]$, linguistic variables of the output are *NB* (negative big), *NM* (negative middle), *NS* (negative small), *Z* (zero), *PS* (positive small), *PM* (positive middle), *PB* (positive big). The membership functions are as shown in Fig. 4 [34].

9. THE FUZZY RULES DESIGN

Fuzzy rules are The core of a fuzzy controller, the object of this roles is to optimize real time parameters of PSO-FPIDC/TLBO-FPIDC controller, the fuzzy rule is depend on expert designers engineers. The convectional PID controller parameter related to characteristic curve, then PID parameter tuning rules set as follows [35]:

1) When the input of PID $\Delta\omega$ is big the speed deviation should be decreta controlled object is established, and the input large, should cancel to realize stability as quickly as possible to improve the dynamic response of system controlled, thus we have to select the big K_P, and we must be careful to avert big $\Delta\omega$ rate differential saturation, so take K_D smaller, this also important to avert big overshoot, so we should take $K_I = 0$.

2) In the medium change of the $\Delta\omega$ and $\Delta\dot{\omega}$ we must minimize the GK_P, GK_I and GK_D and use suitable values.

3) In the system is stable which means the $\Delta\omega$ and $\Delta\dot{\omega}$ is a little, so we must increase the GK_P and GK_I, to enhance the system dynamic, and we must be careful to avert the steady state error, so GK_D effect is very necessary, and generally $\Delta\dot{\omega}$ can take larger GK_D and the large $\Delta\dot{\omega}$ can take smaller GK_D. Related to the pervious tuning steps, then the fuzzy rules shown in Table 1 to Table 3.

10. SIMULATION RESULTS

The proposed controller is applied to a Single Machine Infinite Busbar SMIB power system as shown in Fig. 2. To improve the dynamic stability performance of power system. Speed deviation $\Delta\omega$ and acceleration $\Delta\dot{\omega}$ of the rotor of synchronous generator were taken as input to Particleation Fuzzy PID controller PSO-FPIDC and other type of controllers in stead of conventional power system stabilizer CPSS. Each input has eight fuzzy logical sets [NB, NM, NS, Z, PS, PM, PB]. Thus, total number of input sets are shown in Tables 1-3. The control rules as if $x_1 = A_1^i$, $x_2 = A_2^i$, $x_3 = A_3^i \ldots\ldots x_n = A_n^i$, then $y = B_i$. The output of this controller fed to synchronous generator exciter. The design of PID controller is obtained by using Particle Swarm Optimization PSO and Teacher learner based optimization TLBO [32]. The optimum PID parameters and Fitness function represented in Table 5. the Convergence characteristics of these algorithms shown in Figs. 5-7. we can clearly notice that The PSO based PID controller values offers the best object function F as well as the performance index values. To test the proposed controller step perturbation of 1 [pu] is applied either in reference volt-

Table 1. ΔK_P rules.

$\Delta\omega$	$\Delta\dot{\omega}$						
	ΔK_P						
	NB	*NM*	*NS*	*Z*	*PS*	*PM*	*PB*
NB	*PB*	*PB*	*PM*	*PM*	*PS*	*PS*	*Z*
NM	*PB*	*PB*	*PM*	*PS*	*PS*	*Z*	*NS*
NS	*PM*	*PM*	*PM*	*PS*	*Z*	*NS*	*NS*
Z	*PM*	*PM*	*PS*	*Z*	*NS*	*NM*	*NM*
PS	*PS*	*PS*	*Z*	*NS*	*NS*	*NM*	*NM*
PM	*PS*	*Z*	*NS*	*NM*	*NM*	*NM*	*NB*
PB	*Z*	*Z*	*NM*	*NM*	*NM*	*NB*	*NB*

Table 2. ΔK_I rules.

$\Delta\omega$	$\Delta\dot{\omega}$						
	ΔK_I						
	NB	*NM*	*NS*	*Z*	*PS*	*PM*	*PB*
NB	*NB*	*NB*	*NM*	*NM*	*NS*	*Z*	*Z*
NM	*NB*	*NB*	*NM*	*NS*	*NS*	*Z*	*Z*
NS	*NM*	*NM*	*NS*	*NS*	*Z*	*PS*	*PS*
Z	*NM*	*NM*	*NS*	*Z*	*PS*	*PM*	*PM*
PS	*NM*	*NS*	*Z*	*PS*	*PS*	*PM*	*PB*
PM	*Z*	*Z*	*PS*	*PS*	*PM*	*PM*	*PB*
PB	*PB*	*PM*	*PM*	*PM*	*PS*	*PS*	*PB*

Table 3. ΔK_D rule.

$\Delta\omega$	$\Delta\dot{\omega}$						
	ΔK_D						
	NB	*NM*	*NS*	*Z*	*PS*	*PM*	*PB*
NB	*PS*	*NS*	*NB*	*NB*	*NB*	*NM*	*PS*
NM	*PS*	*NS*	*NB*	*NM*	*NM*	*NS*	*Z*
NS	*Z*	*NS*	*NM*	*NM*	*NS*	*NS*	*Z*
Z	*Z*	*NS*	*NS*	*NS*	*NS*	*NS*	*Z*
PS	*Z*	*Z*	*Z*	*Z*	*Z*	*Z*	*Z*
PM	*PB*	*PS*	*PS*	*PS*	*PS*	*PS*	*PB*
PB	*PB*	*PM*	*PM*	*PM*	*PS*	*PS*	*PB*

Table 4. Controllers parameters.

Type	Parameters									
	GK_P	GK_I	GK_D	K_P	K_I	K_D	K_S	T_W	T_1	T_2
PSO-FPIDC	26.67	13.33	0.533	59.8570	1.7244	1.1697				
TLBO-FPIDC	26.67	13.33	0.533	73.6507	0.00	0.7447				
PSO-PID				59.8570	1.7244	1.1697				
TLBO-PID				73.6507	0.00	0.7447				
CPSS							9.5	1.4	0.156	0.342

Table 5. PID and F values using $PSO/TLBO$.

Iterations	Type	K_p	K_I	K_D	F
50	PSO	60.09	1.2854	2.9431	2.5651
	TLBO	73.622	0	0.7385	2.2917
100	PSO	46.0861	1.4095	0.6257	2.483
	TLBO	81.1486	0.9233	4.3455	2.5281
500	PSO	59.8570	1.7244	1.1697	2.32829
	TLBO	73.6507	0	0.7447	2.5651

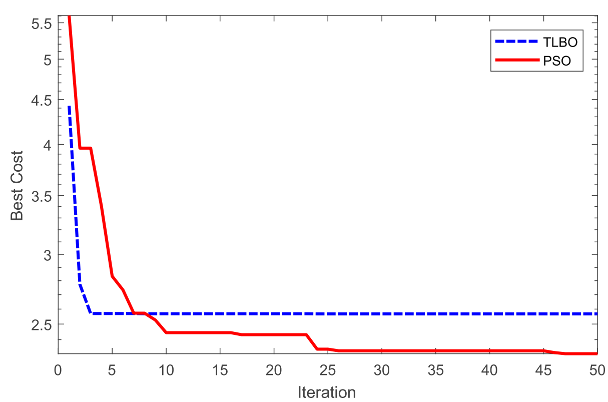

Fig. 5. Convergence of $PSO/TLBO$ under 50 iterations.

age V_{ref} or in mechanical torque T_m simultaneously. The simulation is implemented in MATLAB 17a software.

For the sake of comparison to show the potential merits between the proposed approach The PSO-FPIDC compared with PSO-PID, TLBO-FPIDC, (TLBO-PID) and optimal parameters were determined for CPSS K_s, T_1 and T_2 where these parameters presented in reference [36, 37]. The parameters of all controllers shown in Table 4. Simulation studies are carried out corresponding to an operating condition of P = 0.5, Q = 0.2, $X_e = 0.93$, $E_t = 1.0$(all are in pu) for 1.0 pu under simultaneous change in ΔT_m and ΔV_{ref}. The dynamic responses shown in Figs. 11-16. The comparison between output controller response presented in Figs. 8-10. It is observed from these figures that the proposed controller guarantee stable. Therefore, the PSO-FPIDC controller has the capability to achieve the most

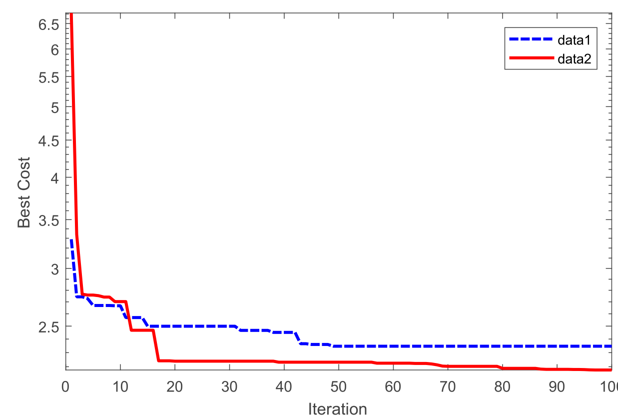

Fig. 6. Convergence of $PSO/TLBO$ under 100 iterations.

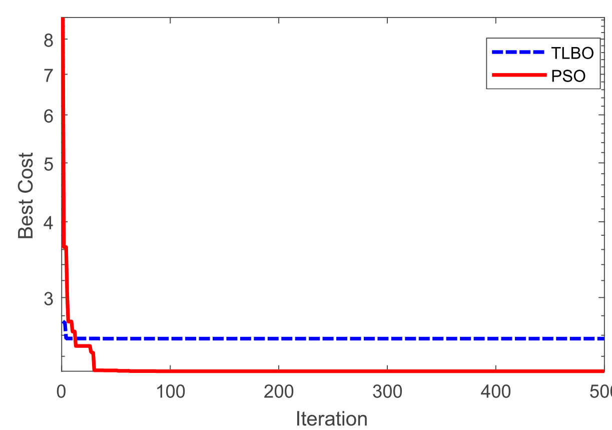

Fig. 7. Convergence of $PSO/TLBO$ under 500 iterations.

(minimum speed oscillations), most stable accurate (minimum O_{sh}/ U_{sh}) and quiet faster (minimum value of rise time t_{rt} and From these figures, it is clearly observed that the transient stabilization performance PSO-FPIDC and TLBO-FPIDC is better than PSO-PID and TLBO-PID and all of the controllers are better performance than CPSS. The dynamic performance presented in Table 6 and Table 7. It is clear appeared that PSO-FPIDC has lower peak over-shoot O_{sh}/ under shoot (U_{sh}, short settling time t_{st} and rise time t_{rt}. So we can say that PSO-FPIDC is the best dynamic performance with respect to other controllers.

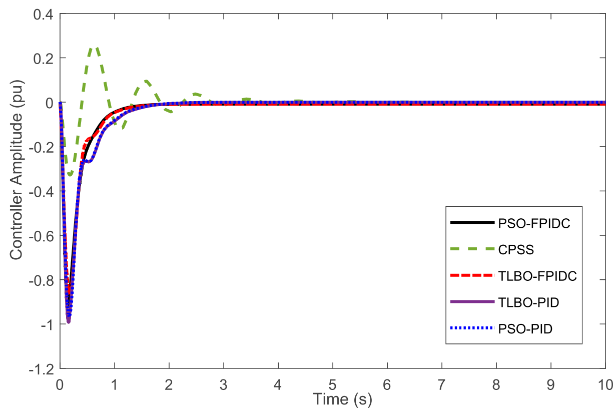

Fig. 8. Controllers response at $\Delta T_m = 0/\Delta V_{ref} = 1$ [pu].

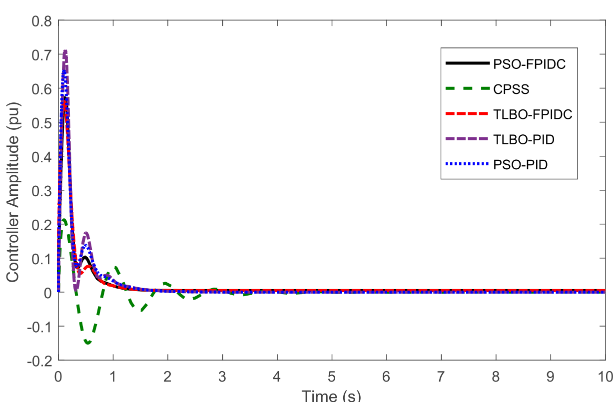

Fig. 9. Controllers response at $\Delta T_m = 1/\Delta V_{ref} = 0$ [pu].

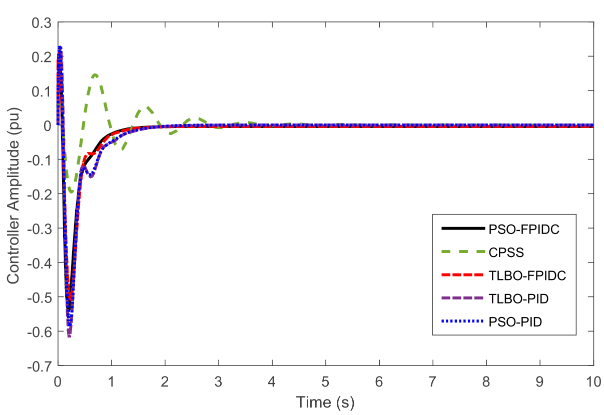

Fig. 10. Controllers response at $\Delta T_m = 1/\Delta V_{ref} = 1$ [pu].

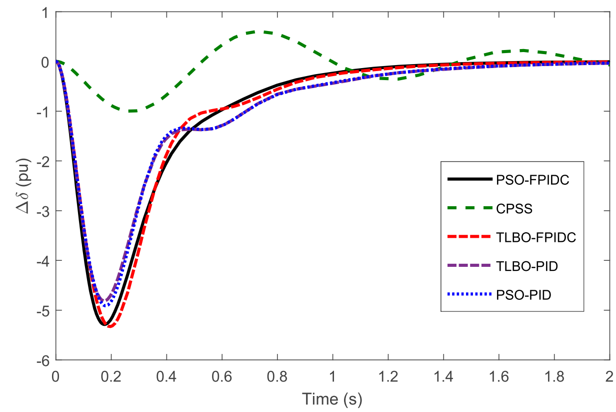

Fig. 11. Dynamic of $\Delta\delta$ when $\Delta T_m = 0$ and $\Delta V_{ref} = 1$ [pu].

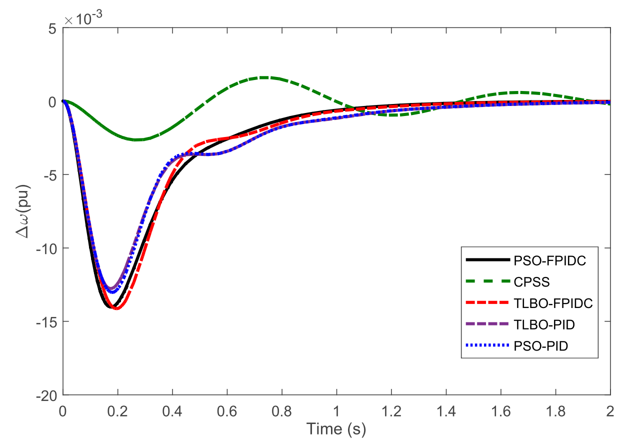

Fig. 12. Dynamic of $\Delta\omega$ when $T_m = 0$ and $\Delta V_{ref} = 1$ [pu].

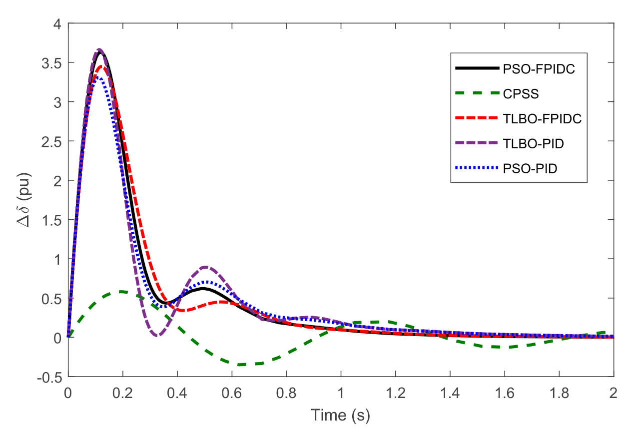

Fig. 13. Dynamic of $\Delta\delta$ when $\Delta T_m = 1$ [pu] and $\Delta V_{ref} = 0$.

11. CONCLUSION

Stability of electric power system can be lost either by lack of synchronizing torque, or due to lack of damping torque oscillatory in due to oscillation caused by external perturbations. In this paper Particle Swarm Optimization Fuzzy PID controller PSO-FPIDC used to enhance the dynamic stability of Single Machine Infinite Busbar system SMIB. The particle swarm optimization PSO and Fuzzy logic Controller FLC was used to optimize the parameters of PID controller we used speed deviation $\Delta\omega$ and acceleration $\Delta\dot{\omega}$ of the rotor as input to Fuzzy PSO-PID controller PSO-FPID, The system examined under different perturbations. The dynamic of the system shows that the PSO-FPIDC has best performance as compared other con-

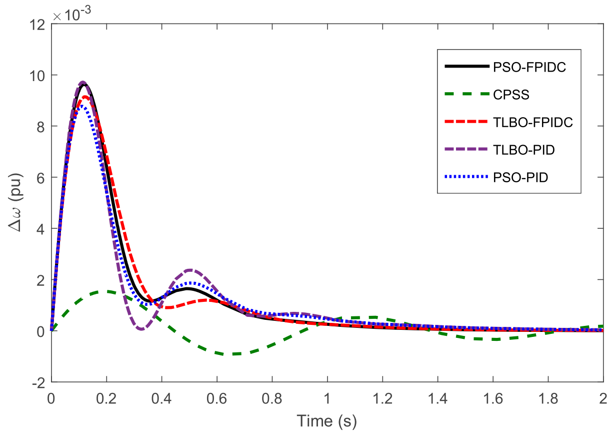

Fig. 14. Dynamic of $\Delta\omega$ when $\Delta T_m = 1$ [pu] and $\Delta V_{ref} = 0$.

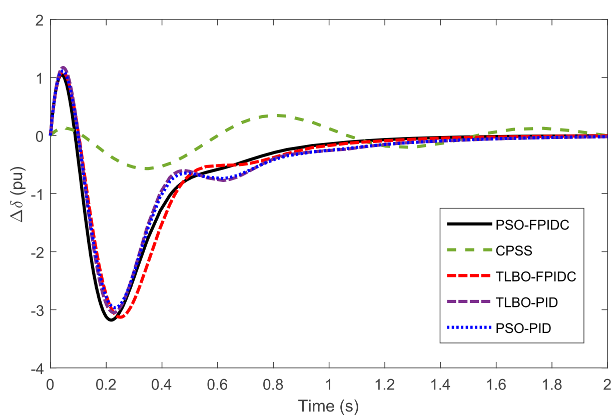

Fig. 15. Dynamic of $\Delta\omega$ when $\Delta T_m = 1$[pu] and $\Delta V_{ref} = 1$ [pu].

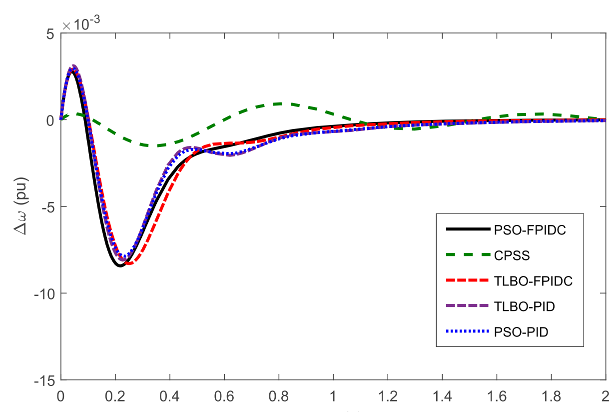

Fig. 16. Dynamic of $\Delta\omega$ when $\Delta T_m = 1$ [pu] and $\Delta V_{ref} = 1$ [pu].

trollers. In future work will try to design adaptive PID and PSS controller using Adaptive TS fuzzy Control which I think it will give good dynamic performance of power system.

Table 6. Performance of $\Delta\delta$ for different controllers.

Step	Type	O_{sh}%	U_{sh} %	t_{rt} [ms]	t_{st} [ms]
$\Delta T_m = 0$,	PSO-FPID	0.490	1.850	847.991	1439
$\Delta V_{ref=1}$	TLBO-FPID	0.079	1.968	208.275	1875
	PSO-PID	0.492	1.849	740.372	2186
	TLBO-PID	0.475	1.750	609.056	2316
	CPSS	75	-2.738	124.065	5533
$\Delta T_m = 1$,	PSO-FPID	0.532	1.859	80.716	1382
$\Delta V_{ref=0}$	TLBO-FPID	0.515	1.849	79.984	1951
	PSO-PID	0.562	1.568	73.158	2030
	TLBO-PID	0.505	1.809	69.595	2005
	CPSS	18.269	1.460	89.8	5043
$\Delta T_m = 1$,	PSO-0FPID	0.137	2.157	213.245	1623
$\Delta V_{ref=1}$	TLBO-FPID	-0.153	1.940	177.808	1746
	PSO-PID	-0.683	1.933	529.519	2275
	TLBO-PID	-0.22	1.912	581.827	2590
	CPSS	60.484	4.984	168.075	5130

Table 7. Performance of $\Delta\delta$ for different controllers.

Step	Type	O_{sh}%	U_{sh} %	t_{rt} [ms]	t_{st} [ms]
$\Delta T_m = 0$,	PSO-FPID	0.476	1.862	488.189	1533
$\Delta V_{ref=1}$	TLBO-FPID	0.079	1.968	208.275	1711
	PSO-PID	0.492	1.849	740.372	2156
	TLBO-PID	0.475	1.750	609.056	2261
	CPSS	75	-2.738	124.065	5089
$\Delta T_m = 1$,	PSO-FPID	0.532	1.859	80.716	1599
$\Delta V_{ref=0}$	TLBO-FPID	0.515	1.849	79.984	1732
	PSO-PID	0.562	1.568	73.158	2127
	TLBO-PID	0.505	1.809	69.595	2016
	CPSS	18.269	1.460	89.800	5096
$\Delta T_m = 1$,	PSO-0FPID	0.137	2.157	213.245	1622
$\Delta V_{ref=1}$	TLBO-FPID	-0.153	1.940	177.808	1711
	PSO-PID	-0.683	1.933	529.519	2022
	TLBO-PID	-0.022	1.912	551.827	2289
	CPSS	60.484	4.984	168.075	5526

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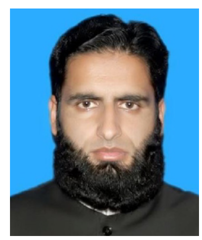

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