

DESIGN OF NONLINEAR OPTIMAL EXCITATION CONTROLLER IN COMPARISON WITH PSO BASED CONVENTIONAL PSS IN POWER SYSTEM STABILITY IMPROVEMENT

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Abstract: This paper focuses on the design of a nonlinear optimal excitation controller in order to improve dynamic stability in a Single Machine Infinite Bus (SMIB) power system. The affine nonlinear model of an SMIB power system is exactly linearized applying feedback linearization method where the optimal control law has been estimated by the Linear Quadratic Regulator (LQR) principle. The performance of the proposed nonlinear excitation control scheme is compared with the performance of the conventional PSS. The parameters of the conventional PSS are designed through a novel soft computation technique, Particle Swarm Optimization (PSO). The results and effectiveness of the design have been presented employing time domain analysis for a typical fault scenario of the study system. It has been observed that, in comparison to the PSO based PSS, significant improvements in dynamic stability of the test power system are achieved by the proposed nonlinear excitation control strategy.

Key words: Approximate Linearization, Exact Linearization, Nonlinear Excitation Control, Particle Swarm Optimization, Power System Stabilizer, Power System Stability.

1. Nomenclature

δ	: rotor angle (degree)
R_e	: transmission line resistance (pu)
ω_0	: synchronous speed (rad./s)
T'_d	: time constant of the field winding
ω	: rotor speed (rad./s)
V_f	: exciter voltage output (pu)
σ	: real part of eigenvalue
V_t	: machine terminal voltage (pu)
D	: damping constant (pu)
V_∞	: infinite bus voltage
$E'q$: voltage behind transient reactance (pu)
X_d	: d -axis synchronous reactance (pu)

H	: inertia constant (s)
X'_d	: d -axis transient reactance (pu)
P_m	: mechanical power (pu)
X_e	: transmission line reactance (pu)

2. Introduction

The enhancement of dynamic stability of a synchronous machine is a challenging problem in modern interconnected power system design. Stable and steady operation of a poorly damped nonlinear power system can be ensured by using high-performance controllers which can regulate the system under diverse operating conditions. It is well known, that the generator excitation control plays an important role in achieving rotor angle stability of power systems [1]. Traditionally, additional damping through excitation control in power systems is introduced by the application of Power System Stabilizers (PSSs) [2]. Though, development of Flexible Alternating Current Transmission System (FACTS) [3] has generated much attention of the researchers in this issue, PSSs are still drawing interest because of its effective and reliable performance [4]. A coordinated control scheme for PSS and FACTS device has been proposed in [5] for damping of power system oscillations in a multimachine power system.

The mathematical model of a power system is generally a high-dimensional nonlinear set of equations [6]. All the previous attempts in [4]-[5] for the design of power system controllers are based on the approximate linearized model of the power system and the analyses are based on the linear control theory. These linear controllers are usually designed to provide satisfactory performance around a single operating condition. However, following

severe contingencies and stressed operating conditions the nonlinear effects of power systems become prominent and the post-contingency system can be significantly different from its nominal operating states. Thus control strategies to be adopted which should reflect the nonlinearity, and be adaptive to uncertainty in order to ensure the improvement of dynamic performance in different operating conditions. In this context, a number of research works regarding nonlinear and intelligent control schemes for power system stability improvement have been addressed in the literatures [7]-[8]. An exact linearization method using optimal parameters is proposed in [9] to nonlinear control of one-machine power system. Some researchers have proposed coordinated control scheme of generator excitation and FACTS controllers. A robust nonlinear co-ordinated generator excitation and TCSC controllers has been reported in [10] to enhance the transient stability of a power systems. A nonlinear control technique, based on zero dynamics is proposed in [11] to design the controller for STATCOM and excitation system co-ordinately. A full-order observer-based excitation controller has been designed in [12] where the control law is estimated for an exactly linearized SMIB power system.

Regarding conventional control scheme, it is well known fact that the design of conventional controllers relies on the availability of accurately tuned parameters and knowledge of the operating condition of the system. Attempts have been made in [13]-[14] to design and application of a conventional PSS based on the robust control theory. Many stochastic search methods such as Genetic Algorithm (GA), Artificial Neural Network (ANN) and Evolutionary Programming (EP) [15]-[16] etc. have been utilized for global optimization problems in power systems. These methods have their individual advantages and drawbacks. Recently, Particle Swarm Optimization (PSO) method [17]-[18] has appeared as a promising algorithm for handling the power system optimization problems. PSO can generate high-quality reliable solutions and has more stable convergence characteristics than other stochastic search methods. The major advantage of PSO is that it has no complex evolution operators such as crossover and mutation like GA.

In this paper first the design of a nonlinear excitation controller has been proposed and then its performance has been compared with the

conventional PSS whose parameters are determined by the PSO based technique. To the best of author's knowledge the proposed work has not been explored in details in the existing literatures.

The paper is organized as follows: Section 3 describes the nonlinear model of a SMIB power system and established the nonlinear control law for excitation control via exact linearization method and LQR principle. The design of a conventional PSS and its parameter optimization algorithm based on PSO has been described in Section 4. The performance and effectiveness of the proposed nonlinear excitation control and its comparison with the conventional PSO based PSS has been examined in Section 5.

3. Design of a Nonlinear Excitation Controller

3.1. Affine Nonlinear Model of a SMIB Power System

To develop the nonlinear excitation control scheme, a simple power system model based on Single Machine Infinite Bus (SMIB) system is adopted in Fig. 1. The equation of motion of a SMIB power system can be described as [19]

$$\dot{\delta} = \omega - \omega_0 \quad (1)$$

$$\dot{\omega} = \frac{\omega_0}{2H} \left(P_m - \frac{D(\omega - \omega_0)}{\omega_0} - \frac{E'_q V_\infty \sin \delta}{X'_{d\Sigma}} \right) \quad (2)$$

$$\dot{E}'_q = -\frac{1}{T'_d} E'_q + \frac{1}{T_d} \frac{X_d - X'_d}{X'_{d\Sigma}} V_\infty \cos \delta + \frac{1}{T_d} V_f \quad (3)$$

where $X_{d\Sigma} = X_d + X_e$, $X'_{d\Sigma} = X'_d + X_e$.

$$T'_d = \frac{T_d X'_{d\Sigma}}{X_{d\Sigma}}.$$

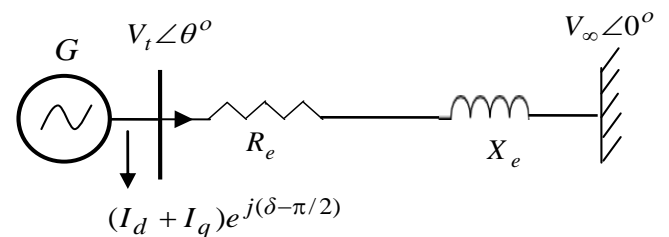


Fig. 1. Single Machine Infinite Bus (SMIB) system

The equations (1)-(3) can be written in an *affine* nonlinear form

$$\dot{x}(t) = f(x) + g(x)u \quad (4)$$

$$y(t) = h(x) \quad (5)$$

where $x = [E'_q \ \omega \ \delta]^T$; $x(0) = [E'_{q0} \ \omega_0 \ \delta_0]^T$

$$f(x) = \begin{bmatrix} -\frac{1}{T_d'} E_q' + \frac{1}{T_d} \frac{X_d - X_d'}{X_d'} V_\infty \cos \delta \\ \frac{\omega_0}{2H} \left(P_{m0} - \frac{D(\omega - \omega_0)}{\omega_0} - \frac{E_q' V_\infty \sin \delta}{X_d'} \right) \\ \omega - \omega_0 \end{bmatrix};$$

$$g(x) = \begin{bmatrix} 1/T_d \\ 0 \\ 0 \end{bmatrix}$$

and $h(x)$ is the vector of the output function. The excitation control input $u = V_f$. Since only the excitation control is considered, assumed here $P_m = P_{m0}$ where P_{m0} is the initial steady state mechanical power. In the following section the nonlinear excitation control law 'u' has been designed with the help of exact linearization of the affine nonlinear model of the power system represented by (4)-(5).

3.2 Exact Linearization and Nonlinear Control Law

The necessary and sufficient condition for exact linearization of an affine nonlinear system is based on the Frobenius theorem [20].

Theorem: Given the system $\dot{x} = f(x) + g(x)u$, whose relative degree r is equal to the system's order n at $x = x_0$, where $x \in R^n$ is the state vector, $u \in R$ the control variable, f and g are both n -dimensional vector fields. The system can be exactly transformed into a completely controllable linear system- a Brunovsky normal form in an open neighbourhood of $x = x_0$, if and only if,

(i) The matrix C is non-singular or the rank of the matrix C does not change and equals n around the neighbourhood of initial value $x = x_0$, where

$$C = [g(x) \ ad_f g(x) \ ad_f^2 g(x) \ \dots \ ad_f^{n-2} g(x) \ ad_f^{n-1} g(x)]$$

(ii) The vector field set D is involutive at $x = x_0$, where

$$D = \{g(x), \ ad_f g(x), \ ad_f^2 g(x) \ \dots \ ad_f^{n-3} g(x), \ ad_f^{n-2} g(x)\}$$

then there exist an "output" function 'w(x)' whose relative degree r is equal to the system's order n at $x = x_0$, which can transform the nonlinear system (4)-(5) into a 'Brunovsky normal form' via exact linearization, and from which one can get the state feedback control law.

According to this theorem an affine nonlinear system given by the equations (4)-(5) of order $n = 3$ is to be exactly linearized if the following matrix $C = [g(x) \ ad_f g(x) \ ad_f^2 g(x)]$ is non-singular around the initial point $x_0 = [E_q' \ \omega_0 \ \delta_0]^T$. The $ad_f g(x)$ and $ad_f^2 g(x)$ can be calculated by the following

relationships; $ad_f g(x) = \frac{\partial g(x)}{\partial x} f(x) - \frac{\partial f(x)}{\partial x} g(x)$ and

$$ad_f^2 g(x) = \frac{\partial(ad_f g(x))}{\partial x} f(x) - \frac{\partial f(x)}{\partial x} ad_f g(x).$$

The matrix C can be obtained as $[C] =$

$$\begin{bmatrix} \frac{1}{T_d} & \frac{X_d \Sigma}{X_d' \Sigma} \frac{1}{T_d} & \frac{X_d^2 \Sigma}{X_d'^2 \Sigma} \frac{1}{T_d^3} \\ 0 & \frac{\omega_0 V_\infty \sin \delta}{2HX_d' \Sigma T_d} & \frac{\omega_s V_\infty}{2HX_d' \Sigma T_d} ((\omega - \omega_0) \cos \delta + (\frac{1}{T_d'} + \frac{D}{2H}) \sin \delta) \\ 0 & 0 & -\frac{\omega_0 V_\infty \sin \delta}{2HX_d' \Sigma T_d} \end{bmatrix}$$

The determinant of the matrix C is then given by

$$\det(C) = -\frac{\omega_0^2 E_q'^2 V_\infty^2 \sin^2 \delta}{4H^2 X_d'^2 T_d^3}.$$

As the value of the above determinant is non-singular for all x in the region,

$\mathfrak{R} = \{E_q' \ \omega \ \delta |, \delta \neq n\pi (n = 0, 1, 2, \dots)\}$, the condition (i) of the given theorem for exact linearization is satisfied.

To check the condition of involutivity, it is need to calculate the 'lie bracket' of $g(x)$ and $ad_f g(x)$ which can be obtained as

$$[g(x), ad_f g(x)] = \frac{\partial(ad_f g(x))}{\partial x} g(x) - \frac{\partial g(x)}{\partial x} ad_f g(x)$$

$$= \begin{bmatrix} 0 & 0 & 0 \\ 0 & 0 & \frac{\omega_s V_\infty}{2HX_d' \Sigma T_d} \cos \delta \\ 0 & 0 & 0 \end{bmatrix} \begin{bmatrix} \frac{1}{T_d} \\ 0 \\ 0 \end{bmatrix} = 0$$

Since null vectors can be a member of any vector field set, the vector field set $D = \{g(x), \ ad_f g(x)\}$ is then involutive, and the condition (ii) of the theorem is satisfied. Thus it is concluded that when the generator rotor angle, $\delta \neq \{0, \pi\}$, the nonlinear

excitation system can be exactly linearized using state feedback.

Therefore, based on the exact linearization approach presented in [21], the nonlinear system (4)-(5) can be transformed into a linear and controllable system by means of composite coordinate transformation (Fig. 2) and the state feedback, which transformed the original vector fields $f(x)$ and $g(x)$ of the nonlinear system into a transformed vector fields;

$$\tilde{f}(x) = J_T(x)f(x) = J_T(x) \begin{bmatrix} f_1(x) \\ f_2(x) \\ f_3(x) \end{bmatrix} \quad (6)$$

$$\tilde{g}(x) = J_T(x)g(x) = J_T(x) \begin{bmatrix} g_1(x) \\ g_2(x) \\ g_3(x) \end{bmatrix} \quad (7)$$

where $J_T(x)$ is the Jacobian matrix of the composite coordinate transformation T , which is given by

$$J_T(x) = \begin{bmatrix} -\frac{\omega_0 V_\infty}{2HX'_{d\Sigma}} \sin \delta & -\frac{D}{2H} & -\frac{\omega_0 V_\infty}{2HX'_{d\Sigma}} E'_q \cos \delta \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix}$$

$$\text{and } f_1(x) = -\frac{1}{T'_d} E'_q + \frac{1}{T'_d} \frac{X_d - X'_d}{X'_d \Sigma} V_\infty \cos \delta,$$

$$f_2(x) = \dot{\omega}, \quad f_3(x) = \omega - \omega_0 \quad \text{and } g_1(x) = \frac{1}{T'_d},$$

$$g_2(x) = 0, \quad g_3(x) = 0.$$

The composite transformation T can be calculated in terms of the following formulae

$$z_1^{(n-1)} = f_2^{(n-2)}(w) \Big|_{w=F^{-1}(x)} = T_1(x)$$

$$z_2^{(n-1)} = f_3^{(n-2)}(w) \Big|_{w=F^{-1}(x)} = T_2(x)$$

... ..

$$z_{n-1}^{(n-1)} = f_n^{(n-2)}(w) \Big|_{w=F^{-1}(x)} = T_{n-1}(x)$$

$$z_n^{(n-1)} = w_n \Big|_{w=F^{-1}(x)} = T_n(x)$$

Based on the above transformation T , the following transformations can be obtained easily from equation (6)-(7) as:

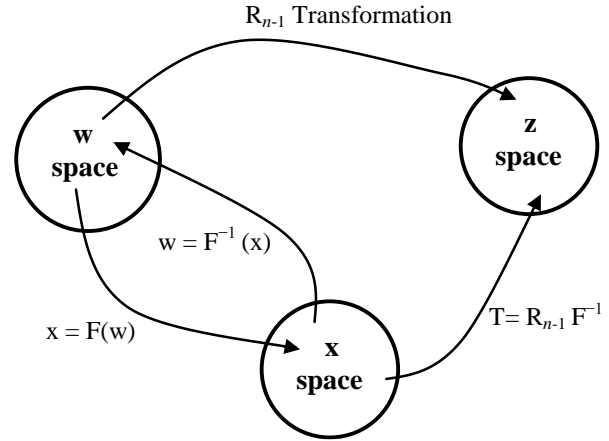


Fig. 2. Composite coordinate transformations among the x , w and z spaces

$$\tilde{f}_1(x) = -\frac{\omega_0 V_\infty}{2HX'_{d\Sigma}} \sin \delta \left(-\frac{1}{T'_d} E'_q + \frac{1}{T'_d} \frac{X_d - X'_d}{X'_d \Sigma} V_\infty \cos \delta \right) - \frac{D}{2H} \dot{\omega} - \frac{\omega_0 V_\infty}{2HX'_{d\Sigma}} E'_q (\omega - \omega_s) \cos \delta \quad (8)$$

$$\tilde{g}_1(x) = -\frac{1}{T'_d} \frac{\omega_0 V_\infty}{2HX'_{d\Sigma}} \sin \delta \quad (9)$$

Thus the final coordinate transformation $z = T(x)$ is given by

$$z_1 = w_3(x) = \delta - \delta_0 \quad (10)$$

$$z_2 = f_3(x) = \omega - \omega_0 \quad (11)$$

$$z_3 = f_2(x) = \dot{\omega} = \frac{\omega_0}{2H} P_{m0} - \frac{D(\omega - \omega_0)}{2H} - \frac{\omega_0 E'_q V_\infty \sin \delta}{2HX'_{d\Sigma}} \quad (12)$$

and the nonlinear state feedback control law of the original system can be achieved as:

$$u = \frac{-\tilde{f}_1(x) + v}{\tilde{g}_1(x)} \quad (13)$$

Such that the system (4)-(5) will be transformed into an exactly linear controllable system in *Brunovsky* normal form,

$$\dot{z}_1 = z_2 \quad (14)$$

$$\dot{z}_2 = z_3 \quad (15)$$

$$\dot{z}_3 = v \quad (16)$$

The *optimal control law* for the above exactly linearized system (14)-(16) can be acquired employing Linear Quadratic Regulator (LQR) principle

$$v^* = -k_1 z_1 - k_2 z_2 - k_3 z_3 = -k_1(\delta - \delta_0) - k_2(\omega - \omega_0) - k_3 \dot{\omega} \quad (17)$$

where the state weighting matrix Q and the control-weighting matrix R are chosen as $Q = \text{diag}(1,1,0)$ and $R = 1$. The system matrix and the input matrix of the exactly linear system are given by $A = [0 \ 1 \ 0; 0 \ 0 \ 1; 0 \ 0 \ 0]$, $B = [0; 0; 1]$ respectively. The optimal constant gain matrix of the controller $k = [k_1 \ k_2 \ k_3]$ is obtained as $k = [1.000 \ 2.299 \ 2.144]$.

Replacing $\tilde{f}_1(x)$ and $\tilde{g}_1(x)$ from (8)-(9) and v^* for v , the nonlinear excitation control law given by (13) becomes

$$u = V_f = \frac{\begin{pmatrix} -\frac{\omega_0 V_\infty}{2HX'_d\Sigma} \sin \delta \left(-\frac{1}{T'_d} E'_q\right. \\ \left. + \frac{1}{T_d} \frac{X_d - X'_d}{X'_d\Sigma} V_\infty \cos \delta\right) - \frac{D}{2H} \dot{\omega} \\ -\frac{\omega_0 V_\infty}{2HX'_d\Sigma} E'_q (\omega - \omega_0) \cos \delta \end{pmatrix}}{-\frac{1}{T_d} \frac{\omega_0 V_\infty}{2HX'_d\Sigma} \sin \delta} + \frac{(-k_1(\delta - \delta_0) - k_2(\omega - \omega_0) - k_3\dot{\omega})}{-\frac{1}{T_d} \frac{\omega_0 V_\infty}{2HX'_d\Sigma} \sin \delta} \quad (18)$$

This nonlinear control law (18) has been simulated in MATLAB in section 5 in order to investigate the dynamic stability of the test power system. The above nonlinear control scheme can be illustrated through a block diagram as shown in Fig. 3.

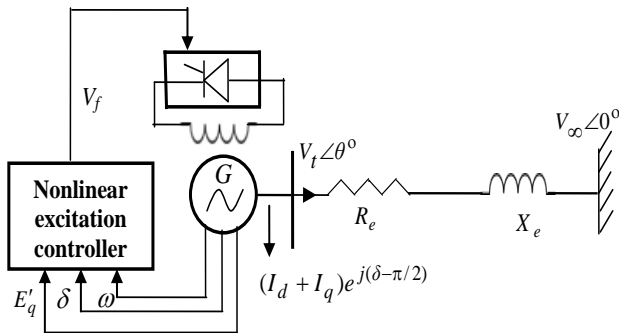


Fig. 3. The block diagram of nonlinear excitation control scheme

4. Design of a Conventional Power System Stabilizer (PSS)

4.1 Model of Power System Stabilizer

The most common configuration of conventional type PSS damping controller is depicted in Fig 4 [22]. The basic function of a PSS is to add damping

to the generator rotor oscillations by controlling its excitation using auxiliary stabilizing signal such as machine speed, terminal frequency or power as input. To mitigate rotor angle oscillations, the PSS must produce a component of damping torque in phase with the rotor speed variations. The controller comprises of a gain block, a signal washout block and a phase compensator block. The signal washout stage ($T_W \approx 10$) is not important for stability analysis and may be included to prevent steady state voltage offset as system frequency changes. The auxiliary control input is the generator speed (ω), and the controlled output is the stabilizing signal (V_s).

The objective is to control the excitation in response to variation of the control input (ω), derived from local measurements. The time constants T_1 , T_2 , T_3 and T_4 should be set to provide damping over the range of frequencies at which oscillations are likely to occur. The transfer function of the PSS given in Fig. 4 can be represented by the following state space equations;

$$\dot{x}_{c1} = -\frac{1}{T_W} x_{c1} + K_{PSS} \dot{\omega} \quad (19)$$

$$\dot{x}_{c2} = \frac{(T_W - T_1)}{T_W T_2} x_{c1} - \frac{1}{T_2} x_{c2} + \frac{K_{PSS} T_1}{T_2} \dot{\omega} \quad (20)$$

$$\dot{V}_S = -\frac{1}{T_4} V_S + \frac{T_3}{T_2 T_4} \frac{(T_W - T_1)}{T_W} x_{c1} + \frac{(T_2 - T_3)}{T_2 T_4} x_{c2} + \frac{K_{PSS} T_1 T_3}{T_2 T_4} \dot{\omega} \quad (21)$$

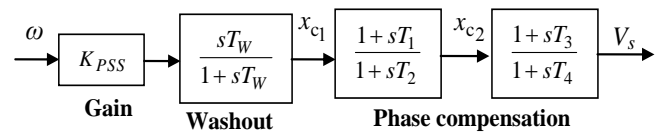


Fig. 4. The transfer function model of a conventional PSS

Therefore, equations (1)-(3) and (19)-(21) together describe the combined state-space model of a SMIB system with PSS. The system matrix (Appendix A.2) and eigenvalues of this system can be determined easily from the approximate linearized model of the combined state-space system. The variable $\dot{\omega}$ in (19)-(21) can be eliminated using machine dynamic equation (2) given in section 3.

There are five tuning parameters of the PSS, the controller gain (K_{PSS}), lead-block time constants (T_1 , T_2) and the lag-block time constants (T_3 , T_4). In the

following section these parameters are optimized employing PSO based method via minimization of a desired objective function. The solution of this problem is difficult to get analytically but the present optimization method solves it avoiding computational complexity.

4.2 Optimization Problem

The optimization problem presented here is to search the optimal parameter set of the PSS employing PSO. It is worth mentioning that the purpose of design of the PSS is to minimize the rotor angle oscillations after a disturbance so as to improve the dynamic stability of the power system. Therefore, this problem can be formulated as a minimization of a desired objective function, critical damping index (*CDI*), which is given by:

$$CDI = J = (1 - \mu) \quad (22)$$

where, $\mu = -\sigma / \sqrt{\sigma^2 + \omega^2}$ is the damping ratio of the critical swing mode. The maximization of the damping ratio ' μ ' results in minimization of ' J '. The value of μ and hence J are determined from the eigenvalue analysis of the system matrix of the combined state space model of the SMIB system with PSS.

The objective of the optimization problem is to maximize the damping ratio (μ) as much as possible. With the change of parameters of the PSS the damping ratio (μ) as well as J varies. The constraints of optimization are set with the possible range of the controller parameters. Therefore, the optimization problem can be stated as:

$$\text{Minimize } J \quad (23)$$

Subject to

$$K_{PSS}^{min} \leq K_{PSS} \leq K_{PSS}^{max}; T_1^{min} \leq T_1 \leq T_1^{max};$$

$$T_2^{min} \leq T_2 \leq T_2^{max}; T_3^{min} \leq T_3 \leq T_3^{max}$$

$$T_4^{min} \leq T_4 \leq T_4^{max}$$

4.3 Algorithm for Implemented PSO

The application of Particle Swarm Optimization method was started around in 1995 [23]. The PSO toolbox available in MATLAB [24] has been used to solve the present optimization problem. The PSO toolbox consists of a main program associated with a bunch of sub-programs and routines which are utilized as per requirements of the problem. The main program '*pso_Trelea_vectorized.m*' has been

implemented here for '*Common*' type PSO as a generic particle swarm optimizer. To find the optimal value of the controller parameters and the objective function (J), this main program runs the user defined eigenvalue computation program. A default plotting routine '*goplotpso.m*' is used by the PSO to plot the best value of the objective function '*gbest*' for the specified generation (epochs) limit.

The '*particle*' can be defined as a vector which contains parameters of the power system stabilizer; $K_{PSS}, T_1, T_2, T_3, T_4$. The initial population is generated randomly for each particle and is kept within a typical range given in second column of Table 2 [19]. The values of these parameters are updated by PSO in each generation within this specified range. The particle configuration for entire population of size N is created repeating it N times as shown in Fig. 5. The objective function corresponding to each particle is evaluated by the eigenvalue analysis program of the test system (Fig. 1).

The algorithms of the implemented PSO have been described here in following steps;

Step 1: Indicate parameters for PSO, population size, generation limit, dimension of input variables, PSO type etc.

Step 2: Generate initial population for the PSS parameters: K_{PSS}, T_1, T_2, T_3 , and T_4 .

Step 3: Run MATLAB program for computation of the system matrix, eigenvalue and the corresponding damping ratio (μ) of the critical swing mode of the proposed test system.

Step 4: Execute objective function (J) for the each '*particle*' in a current population.

Step 5: Determine and store best value of the particle which minimizes the objective function.

Step 6: Check whether the generation exceeds maximum limit.

Step 7: If generation < max. limit, update population for next generation and repeat from step 3.

Step 8: If generation > max. limit, stop program and produce output.

The program parameters for PSO to be set in PSO algorithm are given in Table 1. Choice of these parameters affects the performance and speed of convergence of the algorithm. The rate of convergence of the objective function ' J ' towards the best feasible solutions with particle size 10 and number of generations 150 has been shown in Fig. 6. The final convergence is guaranteed by observing the value of J , which remains unchanged up to 8 decimal

places. The PSO generates optimal values of the controller parameters which are presented in third column of Table 2. The performance of this PSO based PSS respect to the nonlinear excitation controller has been investigated in the following section.

Table 1
Parameter set to implement PSO algorithm

PSO Parameters	Value	PSO Parameters	Value
Swarm Size	10	Epochs before error gradient criterion terminates run	100
Dimension of inputs	5	acc_1, acc_2	2, 2
Maximum generation (epoch)	150	w_{start}, w_{end}	0.9, 0.4
Number of Particles	5	$rand_1, rand_2$	(0, 1)
Minimum error gradient terminates run	$1 \times e^{-8}$	PSO Type	Common '0'

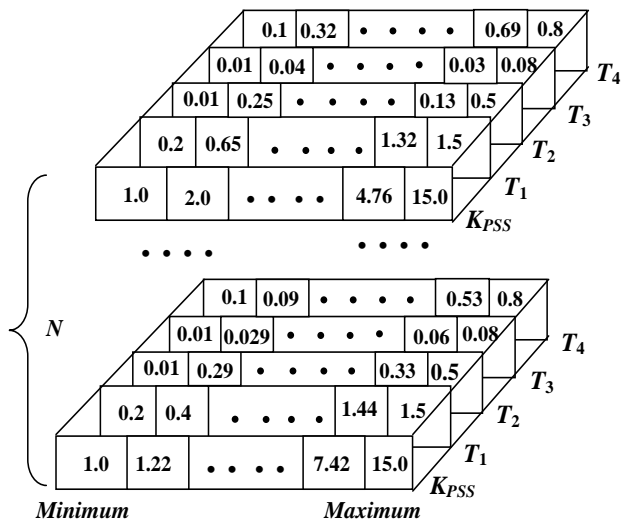


Fig. 5. Particle configuration for entire population

5. Nonlinear Simulation

In order to quantitatively investigate the performance of the proposed nonlinear control scheme, the test system (Fig. 1) was simulated for a given fault scenario. A three-phase-to-earth fault is applied near the generator bus bar at $t = 1.0$ sec and it clears successfully within 20 ms. It can be seen that the rotor angle of the generator increases drastically

following the predefined fault and the system become unstable during first swing. The post fault system returns to stable operation after clearance of the fault. It has been observed from the Fig. 7(a) that the oscillations of generator rotor angle (δ) and its settling time is successfully improved when equipped with the proposed nonlinear excitation control in contrast to the PSO based conventional PSS control.

Table 2
Range of PSS parameters and its PSO based value

Controller parameters	Typical range (Min, Max)	PSO based value
K_{PSS}	1.0, 15.0	7.937
T_1	0.20, 1.50	0.210
T_2	0.01, 0.50	0.041
T_3	0.01, 0.08	0.080
T_4	0.10, 0.80	0.10

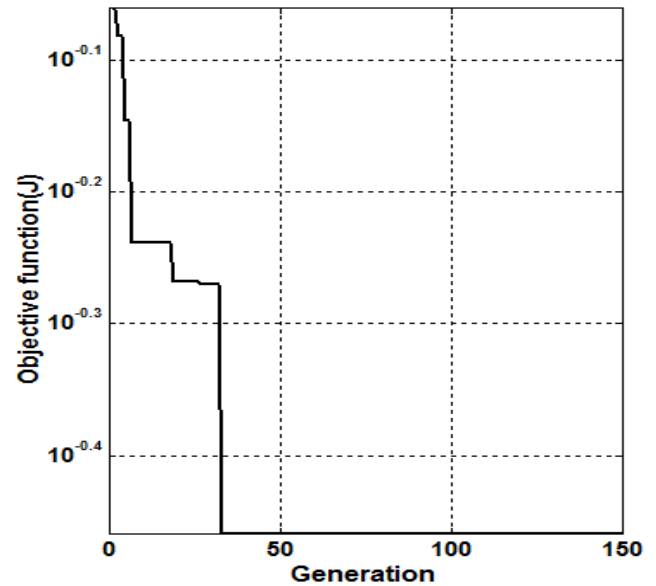


Fig. 6. Convergence of the objective function (J) with PSO

The generator speed response of the post-fault system is also calculated for a simulation time 10 sec. The plot in Fig. 7(b) demonstrates the variation of generator speed with conventional as well as nonlinear excitation controller. It is clear that the system without control losses transient stability with a three-phase-to-earth fault and after clearance of the fault it achieves steady state with application of both PSS and the nonlinear excitation control but the damping and settling time is found to be much satisfactory for the application of later.

The active power response of the system is also studied for similar disturbance. The plot of active

power response is presented in Fig. 7(c). This result also indicates that the dynamic performance, the lasting time of transient response and the number of oscillations have been improved significantly if the nonlinear control strategy is adopted.

Based on the above results it is possible to conclude that the nonlinear excitation controller is more effective and can improve more rapidly dynamic stability of the power system compared with the PSS, even under large disturbances.

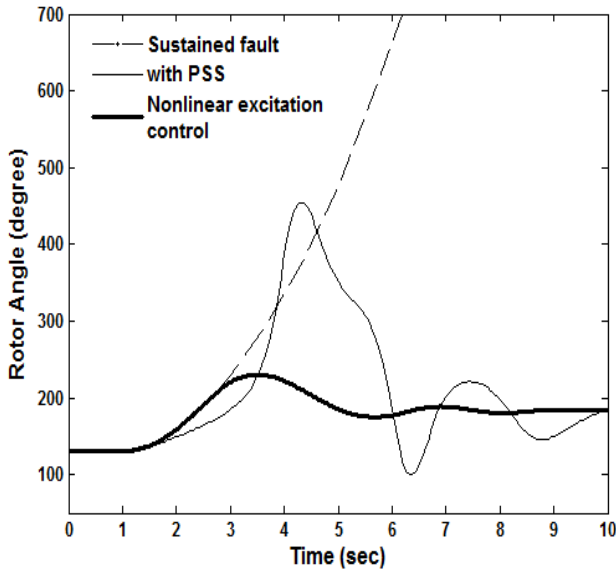


Fig. 7 (a)

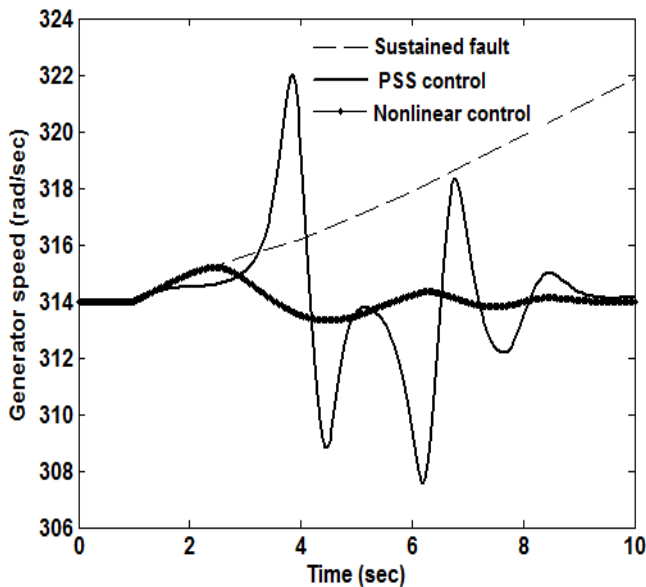


Fig. 7(b)

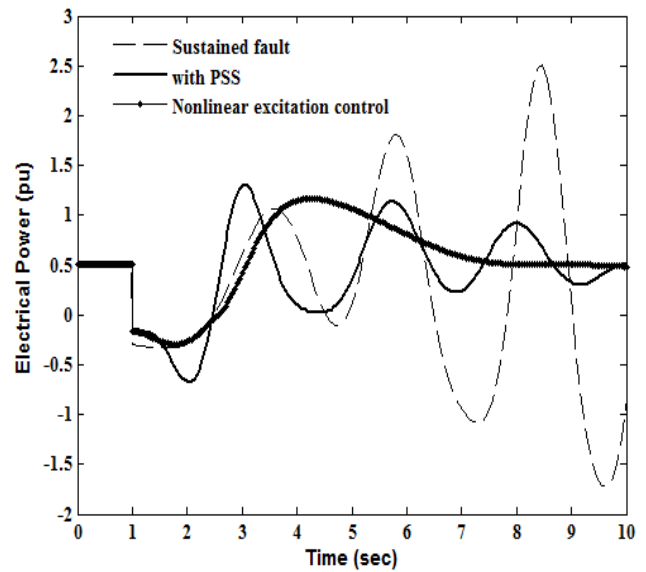


Fig. 7(c)

Fig. 7. Simulation results for improving transient stability with different operating scenarios; (a) Rotor angle response (b) Generator speed response (c) Active power response

6. Conclusions

In this paper a nonlinear control strategy for excitation control has been proposed in order to improve dynamic stability in a SMIB power system. The nonlinear control law has been designed with the help of exact feedback linearization. The optimal gain parameter of the feedback controller has been estimated through LQR principle. The performance of the proposed nonlinear excitation controller has been compared with the conventional PSS. A novel stochastic search method, PSO has been implemented for optimal parameter setting of the conventional PSS via minimization of a desired objective function which is formulated based on the eigenvalue analysis of the test power system. It has been revealed that the nonlinear excitation control scheme is more effective and superior to the conventional PSS in mitigating dynamic instability of SMIB power system. The proposed nonlinear and the conventional control schemes can also be implemented for other power system controllers and for the multimachine power system as a future scope of the work.

Appendix A

A.1 Proposed study system

$H = 2.37\text{sec}$; $D = 0.0$; $R_s = 0.0\text{ pu}$; $R_e = 0.02\text{ pu}$; $T_d = 5.90\text{ sec}$; $\omega_s = 314\text{ rad/sec}$; $X_d = 1.70\text{ pu}$; $X'_d = 0.245\text{ pu}$; $X_e = 0.7\text{ pu}$; $X_q = 1.64\text{ pu}$; $V_{inf} = 1.00 \angle 0^\circ\text{ pu}$; $V_t = 1.72 \angle 19.31^\circ\text{ pu}$.

A.2 System matrix of the approximately linearized system

$$A_{\text{sys}} = \begin{bmatrix} -\frac{1}{T'_d} & 0 & -\frac{1}{T_d} \frac{(X_d - X'_d)V_\infty \sin \delta}{X'_d \Sigma} & 0 & 0 & \frac{1}{T_d} \\ -\frac{1}{2H} \frac{\omega_s V_\infty \sin \delta}{X'_d \Sigma} & -\frac{D}{2H} & -\frac{1}{2H} \frac{\omega_s E'_q V_\infty \cos \delta}{X'_d \Sigma} & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 \\ -\frac{K_{PSS}}{2H} \frac{\omega_s V_\infty \sin \delta}{X'_d \Sigma} & -\frac{K_{PSS} D}{2H} & -\frac{K_{PSS}}{2H} \frac{\omega_s E'_q V_\infty \cos \delta}{X'_d \Sigma} & -\frac{1}{T_W} & 0 & 0 \\ -\frac{K_{PSS} T_1}{T_2} \frac{\omega_s V_\infty \sin \delta}{2HX'_d \Sigma} & -\frac{K_{PSS} T_1}{T_2} \frac{D}{2H} & -\frac{K_{PSS} T_1}{T_2} \frac{\omega_s E'_q V_\infty \cos \delta}{2HX'_d \Sigma} & \frac{(T_W - T_1)}{T_W T_2} & -\frac{1}{T_2} & 0 \\ -\frac{K_{PSS} T_1 T_3}{T_2 T_4} \frac{\omega_s V_\infty \sin \delta}{2HX'_d \Sigma} & -\frac{K_{PSS} T_1 T_3}{T_2 T_4} \frac{D}{2H} & -\frac{K_{PSS} T_1 T_3}{T_2 T_4} \frac{\omega_s E'_q V_\infty \cos \delta}{2HX'_d \Sigma} & \frac{(T_W - T_1) T_3}{T_W T_2 T_4} & \frac{(T_2 - T_3)}{T_W T_2 T_4} & -\frac{1}{T_4} \end{bmatrix}$$

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