# A NOVEL APPROACH TO POWER SYSTEM STABILIZER TUNING USING SPARLS ALGORITHM

**A.Ragavendiran * R. Gnanadass** and K. Ramakrishnan*****
Department of Electrical and Electronic Engineering, Pondicherry Engineering College, Pondicherry, INDIA
*ragavendiran.as@gmail.com,**gnanadass@yahoo.com

**Abstract**
Generators have to meet the change in real and reactive power demand of practical power system. The real power variations in the system are met out by the rescheduling process of the generators. But there is a huge trust to meet out the reactive power load demand. The excitation loop of the corresponding generator is adjusted with its electric limits to activate the reactive power of the network. To expedite the reactive power delivery, power system stabilizer (PSS) is connected in the exciter loop of the generator for various system conditions. In this paper, a new Sparse Recursive Least Square (SPARLS) algorithm is demonstrated to tune the power system stabilizer parameters to meet the vulnerable conditions. The proposed SPARLS algorithm makes use of expectation maximization (EM) updation to tune the PSS. A comparative study between the proposed SPARLS and RLS algorithm has been performed on single machine infinite bus system (SMIB). The simulation results obtained will validate the effectiveness of the proposed algorithm and the impact of stability studies of the power system operation under disturbances. The SPARLS algorithm is also used to tune the parameters of PSS to achieve quicker settling time for the system parameter such as load angle, field voltage and speed deviation. It is found that the SPARLS is a better algorithm for the determination of optimum stabilizer parameter.

*Key-words***:** Power system stabilizer, PID controller, RLS algorithm, SPARLS algorithm, SMIB system, EM method.

## 1. Introduction

In a power system, low frequency oscillation is one of the most important phenomena that occur in a dynamical system. Damped oscillations are contributing an important role in power system. These oscillations will damp automatically after particular time because both AVR and generator field coil will produce some amount of damping torque. If oscillations are not properly controlled, it will damage the system and the relay pick will block out the generator from the system. In order to, avoid the above mentioned problem, the power system stabilizers are widely used to damp the oscillation of the electrical machines in the power system.

Larsen et al. designed the PSS based linear model of the plant using a particular operating point [1]. However, almost all the power systems are nonlinear and the operating point is changeable which changes with respect to the operating condition. Therefore, the performance of a Conventional Power System Stabilizer (CPSS) may deteriorate under variations that result from nonlinear and time-varying characteristics of the controlled plant. The PSS performance is highly sensitive to wide range operating point when artificial intelligence approaches and fuzzy logic are used to tune the PSS [2-4]. Similarly, artificial neural networks [5] and Neuro-fuzzy based PSS have been presented to tune the PSS in [6-7]. The application of robust control methods for designing PSS has been presented in [8-10] and adaptive control algorithms based PSS are presented in [11-13].

Most of the adaptive PSS proposed so far have the signal-synthesizing problem with self tuning controller. A self tuning PID excitation controller is proposed in this paper to improve the damping of a synchronous machine. Tabatabaei et al. proposed a comparative study to analysis the performance of PI and PID controller [14], and from the analyze, the author has demonstrated that the PID controller is giving better dynamic response than a PI controller. To tune the PID, various self tuning methods have been proposed, such as Particle swarm optimization, Genetic algorithm, Fuzzy logic and pole placement non linear programming techniques [15-17]. The recursive fuzzy identification approach is used to tune the PSS for a complex nonlinear system as in [18]. The recursive least square and genetic algorithm are used together to tune the PID controller. The recursive least square (RLS) developed to estimate the system parameters. The genetic algorithm (GN) is developed to tune the system parameters. Both RLS and GN algorithms are established in the ladder programming environment [19]. The above mentioned methods are computationally complex and the solution requires a large number of iterations. In general, the RLS algorithm cannot force any limits on the input parameter formation. As an effect of this simplification, the computation complexity is ($M^2$) per time iteration (where $M$ is the size of data matrix). This becomes the major drawback for their applications as well as for their cost effective implementation. Therefore, to tune the PSS in an interconnected system, less complexity with less iteration is required**.** When comparing the above mentioned drawbacks method with RLS technique, it is less iteration with the fast converging method but computationally complex one. The Sparse RLS algorithm is compared with the RLS, a technique which is less computational complexity and fast converging. The sparse vectors require less time to converge [20 & 21].

In this paper, Single machine infinite bus system and power system stabilizer have been modelled using Simulink block sets. The performance of the PSS and PID has been demonstrated on the SMIB system. The characteristic behavior of the conventional RLS is compared with SPARLS when subjected to different case studies on the above test system. The outline of the paper is as follows: First section describes the necessity of PSS and detailed state of the art about its performance. Section 2 describes the optimization of the power system stabilizer and PID controller structures. The brief background of the SPARLS algorithm is given in the Section 3. Section 4 discusses the single machine infinite bus system. Simulation results are provided in the Section 5. Finally, the conclusions are presented in the Section 6.

## 2. Power System Stabilizer

The function of a PSS is to produce a component of electrical torque in the synchronous machine rotor that is proportional to the deviation of the actual speed from synchronous speed. When the rotor oscillates, this torque acts as a damping torque counter to the low frequency power system oscillations [4]. The structure of a power system stabilizer is shown in Fig. 1. The model consists of a general gain, a washout high-pass filter, a phase-compensation system, and limiter blocks.

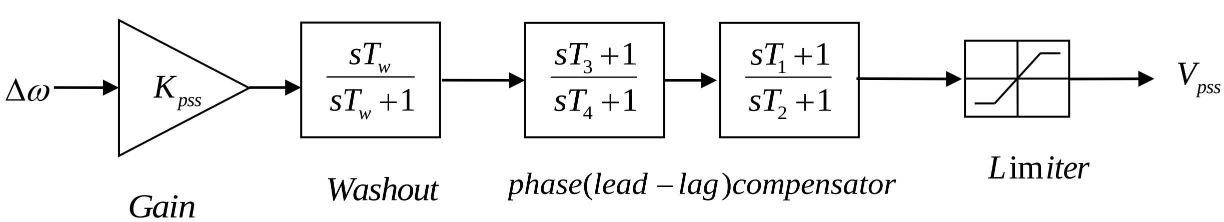


Fig. 1: Block diagram of the Power system stabilizer

The installation of the PSS is provided to improve the power system oscillations. It provides the electrical damping torque in phase with speed deviation to improve power system damping. PID controller is used for stabilization in this system. The input of this stabilizer is speed changing being modelled from the generator. The stabilizer output is stabilizes voltage. The washout time constant (Tw) value should be highly sufficient to allow signals that are connected with oscillations in rotor speed to pass unchanged. From the point of view of the washout function, the value of Tw is not essential and may be in the range of 1s to 20s [21].

$$V_{pss} = K_{pss} \frac{sT_w}{1+sT_w} \frac{1+sT_1}{1+sT_2} \frac{1+sT_3}{1+sT_4} \quad (1)$$

Where

PSS gain

$$K_{pss} = \frac{2\tau\omega_n M}{T(s)|G_e|} \quad (2)$$

Where $\omega_n = \sqrt{k_1\omega_b / M}$ , $G_c = \frac{1+sT_1}{1+sT_2} \frac{1+sT_3}{1+sT_4}$

T (S) is evaluated at $S = j\omega_n$, damping ratio $\tau$ = 0.5 is obtained

Lead lag time constants

$T_1 = \alpha T_2$

Where $\alpha = \frac{1+\sin\beta}{1-\sin\beta}$ , $T_2 = \frac{1}{\omega_n\sqrt{\alpha}}$

Conventional PSS provides effective damping only on a particular operating point. But PSS cannot damp a wide range operating points. PID based PSS provides good damping for a wide range of operating points. The function of PID controller has been discussed /brought in the next section.

## 2.1 PID Controller

PID controller damps out the system over shoot and minimizes settling time. In the PID controller, P element is proportional to the present error. I element is the sum of the past error. D element is taking into account the error evolution which could be considered as the future error. It is used as a feedback controller and its gains varies for different working conditions.

The transfer function of a PID controller is described as follows

$C(s) = K_P + K_I / S + K_D S$ (3)

The self tuning gains of the PID controller [22]

$$K_P = (s_1 + 2s_2)/(1+r_1) ,$$

$$K_I = -(s_0 + s_1 + s_2)/T_s \text{ and}$$

$$K_D = \left\{\left[r_1 s_1 - (1-r_1)s_2\right]/(1+r_1)\right\} T_s . \quad (4)$$

Where $s_0$, $s_1$, $s_2$ and $r_1$ are algorithm estimated values [22].

In this paper, self tuning PSS and PID controller are proposed by RLS and SPARLS algorithm. The RLS algorithm is used for automatic tuning of PSS and PID controller. The Recursive Least Square is one of the basic and fast converging methods used for automatic tuning of PSS and PID controller, but computationally this is the complex algorithm.

## 3. Problem Formulation

The standard industrial approach to power system modelling for PSS design is based on the set of nonlinear differential algebraic equations in the form given in [22].

$$\dot{x}(t) = f\left(x(t), u(t), z, \lambda\right) \quad (5)$$

$$0 = h\left(x(t), u(t), z, \lambda\right) \quad (6)$$

$$y(t) = g\left(x(t), u(t), z, \lambda\right) \quad (7)$$

Where $x(t) \in \mathbb{R}^n$ is the system control input, $y(t) \in \mathbb{R}^p$ is the system output, $z$ is a vector of algebraic variables representing the transmission network coupling among the states of different generators and $\lambda$ is a vector of parameters representing the load levels and other quantities defining the system operating condition. The control problem is formulated by using equations (5)–(7) to emphasize the general applicability of the proposed solution, and more details on the model that is used to validate the effectiveness of the proposed algorithm will be given in Section 4. The algebraic constraint equation (6) can be eliminated from equations (5) – (7), resulting in a linear model in the form

$$\dot{x}(t) = Ax(t) + Bu(t) \quad (8)$$

$$y(t) = Cx(t) + Du(t) \quad (9)$$

In equations (8)–(9), $x(t)$ represents a deviation from an equilibrium value of $x(t)$ with respect to equations (5)–(7), obtained for a particular value of the parameter vector l. Similarly, $u(t)$ and $y(t)$ represent deviations from equilibrium value of $u(t)$ and $y(t)$ respectively. The models treated in this paper, has no direct coupling between the control input $u(t)$ and the measured output $y(t)$, so the term $Du(t)$ can be dropped in equation (9) for the remaining of the text. It is important to emphasize, however, that this coupling exists.

**SPARSE RLS (SPARLS) algorithm**

The term sparse refers to a computable property of a vector. It means that the vector is small in sense but not length that is important. Instead sparsity concerns the number of non-zero entries in the vector. A wide range of attractive estimation problem deals with the estimation of sparse vectors. Many values of attention can naturally be modelled as sparse.

The SPARLS algorithm is used to identify the system parameters and helps to adjust the gains of the PSS/PID controller to bring the stability of the system. The sampling data is generated by executing the system parameters for a specified interval of time. By applying the SPARLS algorithm, a sampling sequence is formed. The optimal system parameter estimation is carried out by obtaining the mean value of the two successive moments of sampling. The forming and description of the SPARLS sampling is explained as follows:

Let the system model (4) is given in the form

$$Ay(m) = Bx(m-1) \quad (10)$$

where $x(m-1)$ is a discrete delay input signal, $y(m)$ is discrete output signal, and

consider a system described by its input output relationship

$$y(m) + a_1 y(m-1) + a_2 y(m-2) = b_1 u(m-1) + b_2 u(m-2)$$

Which is co-efficient estimation by RLSmethod

$$A(z^{-1})y(z^{-1}) = z^{-1}B(z^{-1})u(z^{-1})$$

Where $z^{-1}$ is the backward shift operation.

The value of the polynomials for the above discrete function is determined as follows:

$$A(z^{-1}) = 1 + a_1 z^{-1} + a_2 z^{-2} + \cdots\cdots\cdots + a_{na} z^{-na} \quad (11)$$

$$B(z^{-1}) = b_0 + b_1 z^{-1} + b_2 z^{-2} + \cdots\cdots\cdots + b_{nb} z^{-nb} \quad (12)$$

where $A$ and $B$ are polynomials. $a_1....a_{na}$ and $b_0.b_1...b_{nb}$ are co-efficient of polynomials. A generalized model of the system (2) can be presented in the following form

$$y(m) = u^T \theta \quad (13)$$

where $\theta$ is the unknown parameter and $u$ is the known parameter. The unknown parameters are defined as

$$u^T = [-a_1 \cdots - a_{na}, b_0 \cdots b_{nb}] \quad (14)$$

This consists of measured values of input and output

$$y^T(m) = [\, y(m-1) \cdots y(m-na), x(m-1) \cdots x(m-nb-1)] \quad (15)$$

where

$y(m-1) \cdots y(m-na), x(m-1) \cdots x(m-nb-1)$ are delayed input and output variables. An accurate description of the system can be obtained by the model (5). Hence, the system parameters θ should be determined from the output and input of signal samples at the system.

$$y(m) = u^T(m)\hat{\theta} + e(m) \quad (16)$$

where $\hat{\theta}$ is a vector of unknown sampling parameter of the system, and $e(m)$ is an error in the modelling. $\hat{\theta}$ should be correctly identified so as to minimize the modeling uncertainties.

From the equation 1 & 4, the error is obtained as

$$e(m) = x(m) - d(m) \quad (17)$$

The canonical form of the problem typically assumes that the input-output sequences are generated by a time varying system with parameters represented by $w(m)$. Thus the process is described by an estimate of the desired model

$$d(m) = w(m)y(m) + \eta(m) \quad (18)$$

Where $\eta(m)$ is the observation error. $d(m)$ is the desired output of the filter at time $m$. The error will be assumed to be random error. The estimator has only access to the streaming parameter $x(m)$ and $d(m)$. $d(m)$ value is substituted in the error equation (6), the error is obtained as

$$e(m) = x(m) - (w(m)y(m) + \eta(m)) \quad (19)$$

The SPARLS algorithm is associated for updating error coefficients so that the SPARLS algorithm can be operated in an unknown parameters and non linear system. The system error characteristic is determined by adjusting system coefficients according to the system parameter conditions and performance criteria assessment. The schematic realization of the Sparse RLS algorithm is shown in Fig. 2.

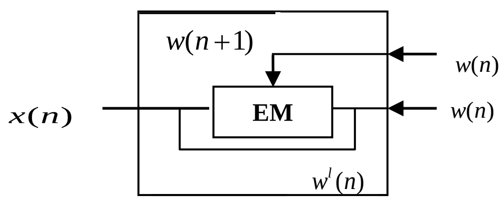


Fig. 2: Schematic diagram of Sparse RLS

The input vector at time $m$ is defined by

$$x(m) = [x(m), x(m-1), ...., x(m-N+1)]^T \quad (20)$$

The weight vector at time $m$ is defined by

$$w(m) = [w_0(m), w_1(m), ....., w_{N-1}(m)]^T \quad (21)$$

The operation of the adaptation at time $m$ can therefore be stated as the following optimization problem

$$\min_{w(m)} = f(e(1), e(2), ...., e(m)) \quad (22)$$

Where $f \geq 0$ is a certain cost performance. With an appropriate choice of $f$, one can possibly obtain a good approximation to $w(m)$ by solving the optimization problem given in above equation. In general, this is an estimation problem.

The Lagrangian formulation shows that if $f = f_{RLS}$, the optimum solution can be equivalently derived from the following optimization problem

$$\min_{\hat{w}(m)} \frac{1}{2\sigma^2} \left\| D(m)^{1/2} d(m) - D(m)^{1/2} X(m)\hat{w}(m) \right\|_2^2 + \gamma \left\| \hat{w}(m) \right\|_1 \quad (23)$$

Where

$$D(m) = \begin{pmatrix} \lambda^{n-1} & \dots & 0 & 0 \\ \vdots & \lambda^{n-2} & \vdots & 0 \\ 0 & \dots & \ddots & \vdots \\ 0 & 0 & \dots & 1 \end{pmatrix}$$

Let $x \in C^N$ be a vector in which most of its weight is distributed on a small number of the total set of vectors known as sparse i.e. A vector $x$ is called sparse, if $\|x\|_0 \ll N$. For any $x$, let $\|x\|_0$ denote the number of non-zero coefficients of $x$. The $l_0$ quasi-norm of $x$ as follows

$$\|w(m)\|_0 = |\{x_n / x_n \neq 0\}|$$

The following cost function

$$f_m(w) = \frac{1}{2\sigma^2} \left\| D(m)^{1/2} d(m) - D(m)^{1/2} X(m)\hat{w}(m) \right\|_2^2 + \gamma \left\| \hat{w}(m) \right\|_1 \quad (24)$$

$$= \frac{1}{2\sigma^2}(d(m) - X(m)w(m))^* D(m)(d(m) - X(m))w(m)) + \gamma \left\| \hat{w}(m) \right\|_1 \quad (25)$$

The expectation maximization algorithm is an efficient technique for the iterative procedure to compute the maximum likelihood estimate in the presence of missing or hidden data. In each iteration, the EM algorithm consists of two steps i.e. E-step and M-step. The maximum likelihood problem is

$$\max_{w(m)} \{\log p(d(m) / w(m) - \gamma \left\| \hat{w}(m) \right\|_1\} \quad (26)$$

This ML problem in general is hard to solve. But by using EM algorithm it is easy to solve. The idea is to decompose the error vector $\eta(m)$ in order to divide the optimization problem. The ℓth iteration of the EM algorithm is as follows

E-step:

$$Q(w|w(m)) = -\frac{1}{2\sigma^2} \left\| r^{(l)} - w \right\|_2^2 - \gamma \|w\|_1 \quad (27)$$

Where

$$r^{(l)}(m) = (I - \frac{\alpha^2}{\sigma^2} X^*(m) D(m) X(m) \hat{w}^{(l)}(m) + \frac{\alpha^2}{\sigma^2} X^*(m) D(m) d(m))$$

where $\sigma = d(m) - x^T(m)w(m-1)$ is the a priori error.

M-step:

$$\hat{w}^{(l+1)}(m) = sign(r^{(l)}(m)) \bullet \left( \left| r^{(l)}(m) \right| - \gamma\alpha^2 I \right) \tag{28}$$

In order to simplify the low complexity implementation of the EM algorithm for $r^{(l)}(m) \in R^N$. Generalization of $r^{(l)}(m) \in C^N$ is straightforward, since the low complexity implementation can be applied to the real and imaginary parts of $r^{(l)}(m)$ independently. Let $I^{(l)}$ be the support of $r^{(l)}(m)$ at the $l^{th}$ iteration. Let

$$I_{\pm}^{(l)} = \{i : r_i^{(l)}(n) > \gamma\alpha^2 \subseteq I^{(l)}$$

$$w_i^{(l+1)}(n) = \left. \begin{matrix} r_i^{(l)} \pm \gamma\alpha^2 & i \in I^{(l)} \\ 0 & i \in I^{(l)} + UI^{(l)} \end{matrix} \right\} \tag{29}$$

For $i = 1, 2, \cdots\cdots, N$.

$$B(m) = I - \frac{\alpha^2}{\sigma^2} x^*(m) D(m) x(m) \tag{30}$$

$$u(m) = \frac{\alpha^2}{\sigma^2} x^*(m) d(m) x(m) \tag{31}$$

$$B(m)w^{(l+1)}(m) = B_{I+}^{(l)}(n)(r_I^{(l)}(n) \pm \gamma\alpha^2 1_{I_{\pm}^l}) \pm \gamma\alpha^2 1_{I_{\pm}^l} + \gamma\alpha^2 1_{I_{-}^l} \tag{32}$$

This new set of iteration has a lower computational complexity, since it restricts the matrix multiplications to the instantaneous support of the estimate $r^{(l)}(m)$, which is expected to be close to the support of $w(m)$. The above equations denote the iterations of low-complexity expectation maximization algorithm. Upon the arrival of the $n^{th}$ input, $B(m)$ and $u(m)$ can be obtained via the following updated rules

$$B(m) = \lambda B(m-1) - \frac{\alpha^2}{\sigma^2} x(m)x(m) + (1-\lambda)I \tag{33}$$

$$u(m) = \lambda u(m-1) + \frac{\alpha^2}{\sigma^2} d(m)x(m) \tag{34}$$

Upon the arrival of the $m^{th}$ input $x(m)$, the SPARLS algorithm computes the estimate $w^{(l)}(m)$ i.e. update the $w^{(l+1)}(m)$ by given $B(m)$ and $u(m)$. The input argument $m$ denotes the number of EM iterations. Without loss of generality, it can set the time index $\eta = 1$ such that $x(1) \neq 0$.

The main objective of SPARLS error cancellation is accomplished by feeding the system output back to the SPARLS algorithm and adjusting the controller through a SPARLS algorithm to minimize the number of input samples, better peak signal to error ratio and convergence time. SPARLS algorithms have the ability to adjust its impulse response to algorithm to find out the correlated signal in the input. It requires the knowledge of the signal and error characteristics. SPARLS algorithms have the capability of SPARLS tracking the signal under non-stationary conditions. Error Cancellation is a variation of optimal algorithm that involves producing an estimate of the error by algorithm the reference input and then subtracting this error estimate from the primary input containing both system response and error.

### 3.3.1 Steps by Step Procedure for SPARLS Algorithm

Step 1. Initialize the reference parameter such as PSS parameter/PID gains.
Step 2. Run the system obtain sample values.
Step 3. Calculate the output y(m) from obtaining parameters using equation (16).
Step 4. The proposed algorithm is an estimation of sparse vectors (26).
Step 5. Estimate error between set value and the desired value.
Step 6. Update the error using equation (34).
Step 7. Calculate the value of PSS parameter.
Step 8. Update the new PSS parameter.
The flow chart of SPARLS algorithm is given in Fig. 3:

## 4. System Description

The demonstrated test system consists of single generator, buses, single 230 KV transmission lines, 100 MW load demand. The one line diagram of the SMIB system is shown in Fig. 4, the synchronous generator is connected with

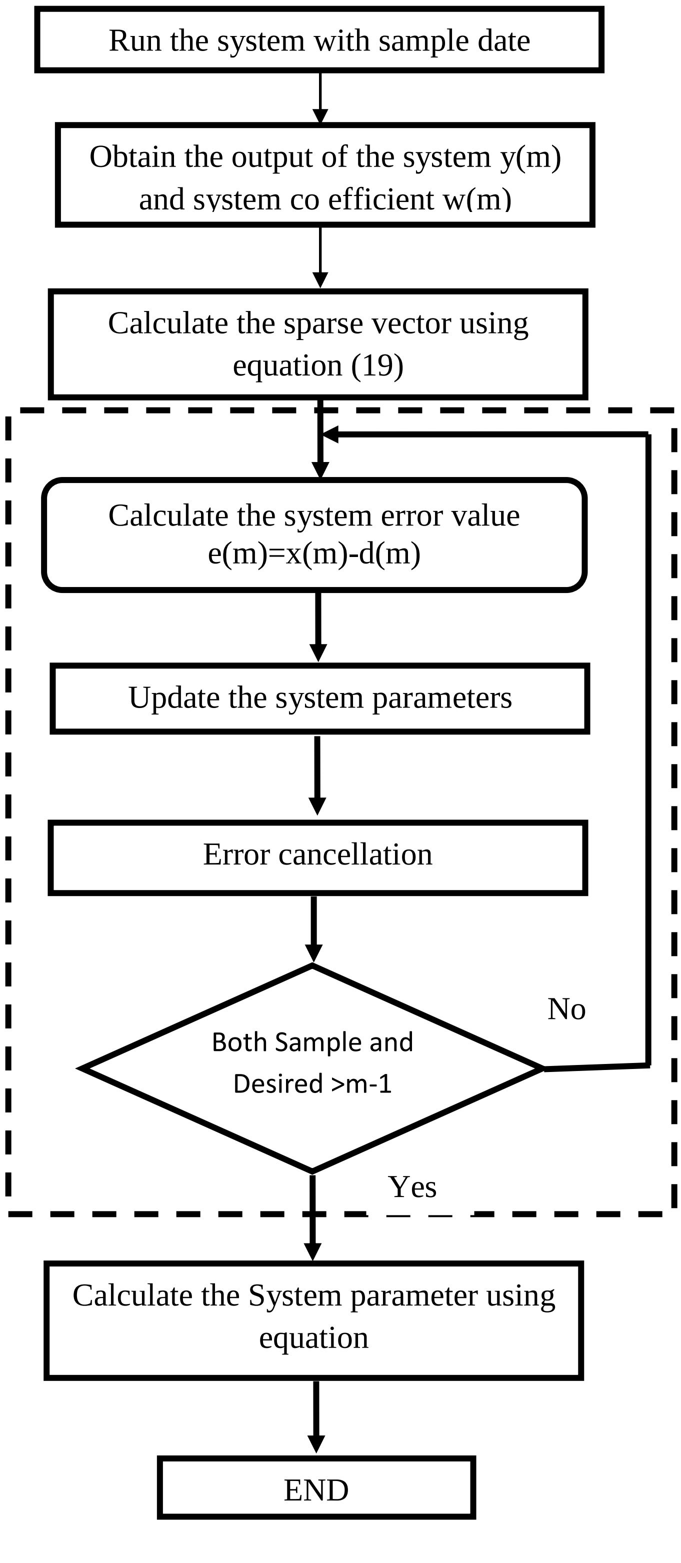


Fig. 3: General flow chart for SPARLS algorithm

the infinite bus through the transmission line. The real power of the synchronous generator is governed by speed governor. The output of the rotor speed deviation governor compares with power reference and given to a turbine which is connected to the synchronous generator. The entire generator units are equipped with the fast-acting static exciters and the speed governors. The PSS is installed in synchronous generators to improve the transient performance after a big disturbance. The rotor speed deviation of synchronous generator is given to PSS as input whose output is used to get stable voltage (Vpss). The stable voltage is given to synchronous generator through the voltage regulator and exciter. The output of voltage of the exciter is given to excitation system stabilizer and is compared with reference to terminal voltage. The output power from the synchronous generator is given to infinite bus through transmission voltage.

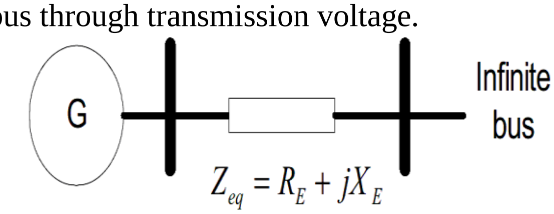


Fig. 4: Single line diagram of a single machine infinite bus system

To analyze the performance of the PSS, a model is developed in simulink block set of MATLAB. The functional block set of PSS is developed in Simulink environment which is given in Fig. 5.

## 5. SIMULATION RESULTS AND DISCUSSION

The performance of PSS, without PSS, RLS & SPARLS based PSS and RLS & SPARLS based PID with PSS was studied in the simulink environment for different operating conditions and the following test cases was considered for simulations.

*Case I:* To normal load the variation of speed deviation, field voltage and load angle were analyzed for PSS, without PSS, RLS &

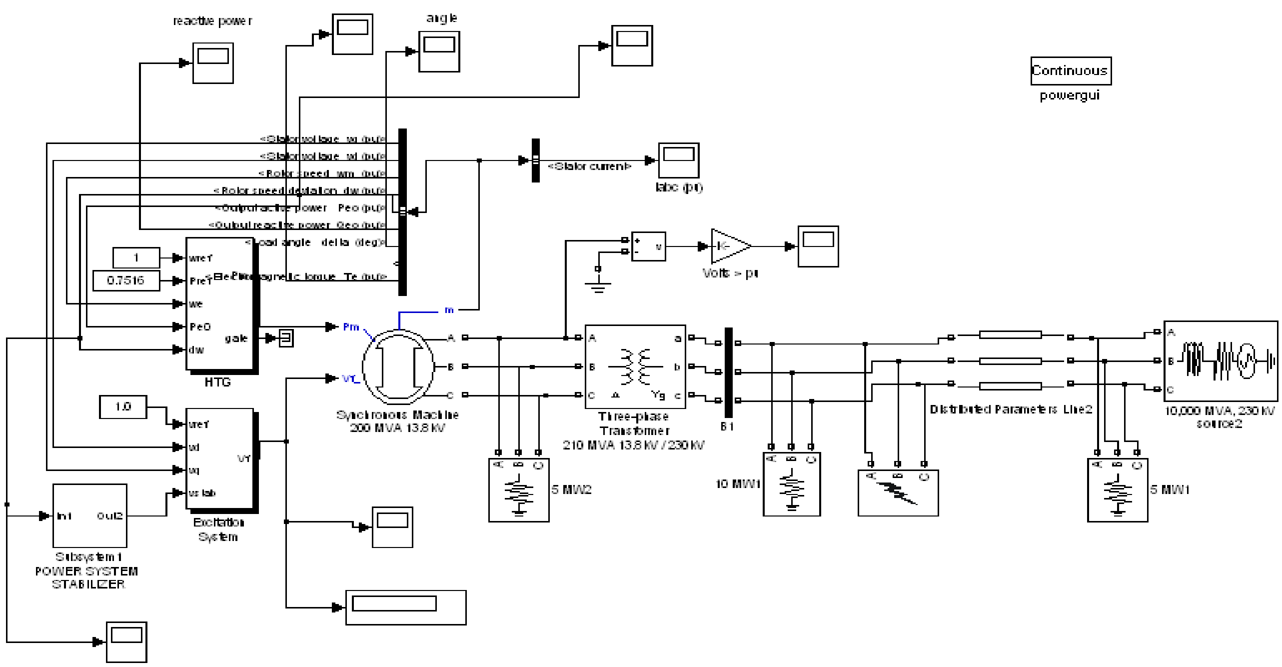


Fig. 5: Simulink diagram of a SMIB system

SPARLS based PSS and RLS & SPARLS based PID with PSS.

*Case II:* The variation of the above mentioned cases was analyzed when system subjected to 50 % increased in loading condition.

*Case III:* System was subjected to fault condition when the variation of above mentioned cases were analyzed.

To illustrate the effectiveness and robustness of the proposed algorithm different possible case studies are explained as follows, the controller reduces the overshoot and settling time to the nominal level when subjected to PSS, without PSS, RLS & SPARLS based PSS and RLS & SPARLS based PID with PSS and the inference of the simulation results are as follows.

### 5.1 Base Load Condition

Here, the synchronous machine subjected to base load of is taken as 100 MW. The PSS is installed in the corresponding exciter loop of all the generator and the performance characteristics is given in Fig. 6 to 12. The performance of PSS was demonstrated on a SMIB system, eleven bus system in the Simulink environment for different operating conditions. Based upon the RLS and SPARLS algorithm PSS based PID gain values are tuned in Matlab simulink. From the Fig. 6 it is observed that the SPARLS based PID with PSS can provide the better damping characteristic than the other cases. The SPARLS based PID with PSS reduced the overshoot and the system reaches the steady state quickly compared to PSS, without PSS, RLS & SPARLS based PSS and RLS based PID with PSS. The speed deviation of the RLS & SPARLS based PID with PSS is shown in Fig. 7 which depicts that the SPARLS based PID with PSS can provide the better damping characteristic than the RLS based PID with PSS. From the Fig. 8, it is observed that the RLS based PID with PSS controller also gives better settling time (2 Secs) compared to PSS, without PSS, RLS & SPARLS based PSS. The SPARLS based PID with PSS further reduces the settling time at 1 Secs and also the overshoot. By this effect, the field voltage (Fig. 9) will be stable and in turn ensures the system stability. In response of Speed deviation Fig. 6, the overshoot reduced to 0.005 from 0.017 using PID with PSS therefore the system reaches the stable state quickly. It is necessary to maintain the speed in the synchronous generator should be make the system reach the steady state as early as possible for that SPRLS based PID with PSS give better optimal solution compared to others. Normally for the smart system the load angle should be maintained around 15 to 45 degrees. From the Fig. 10, the load angle reaches the stable state at 45 degree. Here it is inferred that after the inclusion of SPARLS based PID with PSS the damping oscillation was reduced, it also boosts up the load angle to 45 from 19 degree. According to Fig.10, SPARLS based PID with PSS improves the rotor angle to the maximum extent by reaching the settling time before 1.5 Secs. The performance of SPARLS and RLS in speed deviation is shown in Fig.11. From the results obtained, it is obvious that the speed estimated from the SPARLS tracks closely than actual speed even when there is a change in the parameter. The error in the speed estimation is almost negligible whereas RLS is not closer to the actual speed and fails to control the error in the speed estimator. The SPARLS based speed estimation is shown to overcome the RLS. The error of SPARLS and RLS (Fig. 12) are 0.2 % and 4.5 % respectively.

### 5.2 Increasing in Load Condition

In this case, the Synchronous generator is subjected increased in load of 50% from the base load. The performance characteristics of the system with PSS, PID, PID with PSS and without PSS are illustrated from Fig. 13 to 16. From the base load condition, it is observed that SPARLS based PID with PSS performance is better than the other controller, in this increasing in load condition compared to the RLS & SPARLS are compared based on PID with PSS alone. From the Fig. 13, the SPARLS based PID with PSS provides a better solution by reducing overshoot to 75% and the settling time in 2 secs even in heavy load condition. By this effect the field voltage (Fig. 14) will be stable and it will maintain the system stability. According to Fig. 13, the overshoot was heavy for RLS based PID with PSS and it affects the stability of the system. The SPARLS based PID with PSS reduces the overshoot to 50% and makes the system to reach steady state before 1.5 secs. Therefore it is inferred that PID with PSS supports the synchronous generator to maintain synchronous speed even in increasing load condition. During the load condition, the SPARLS based PID with PSS makes the system to settle in 2 secs. Also it boosts up the system to maintain the load angle in and around 20 degree (Fig. 15). Also in this case, the proposed system also maintains stability. To analyze the performance of RLS and SPARLS the speed deviation estimated for increasing load condition is shown in Fig. 13. The error estimated from RLS and SPARLS is shown in Fig. 16 (b). From the results obtained, it is clearly understood that speed deviation estimated from the SPARLS is very well even in the increasing load, the error is 0.245 %. Thus RLS based speed deviation is found to be less sensitive even in increasing load condition, this is because the RLS algorithm does not force any restriction on the input data formation, whereas speed deviation from the RLS deviated from the actual. It is also noted that the error in the speed deviation keeps on increasing. Thus, from the above analysis, it is understood that SPARLS algorithm exhibits stable performance where as RLS algorithm shows unstable performance. For the comparison, both the figures are shown with same scale. From the results obtained, it is seen that the SPARLS based speed deviation displays stable performance that tracks the actual speed well whereas RLS becomes unstable and fails to reduce error. The SPARLS based speed deviation is shown to overcome the RLS based speed deviation.

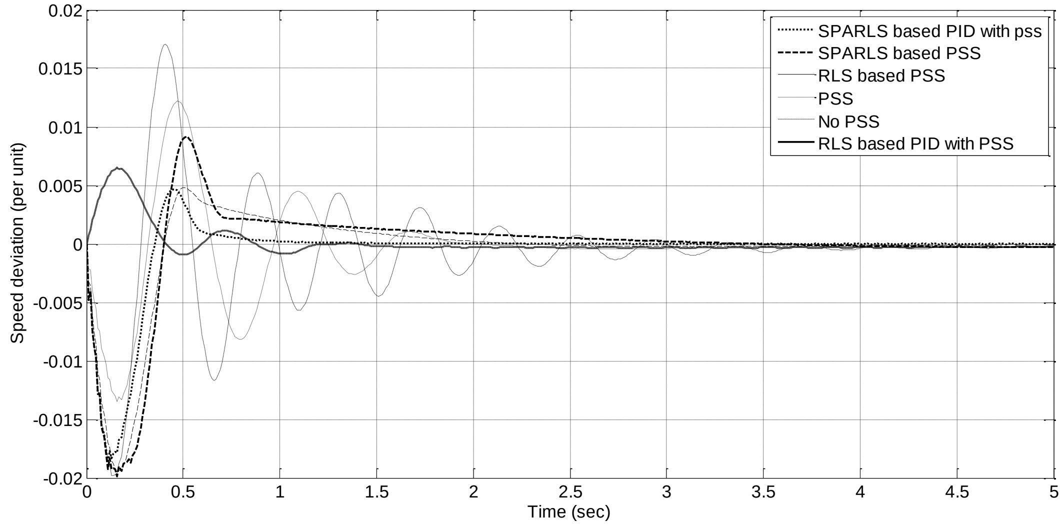


Fig. 6: Speed deviation during base load condition

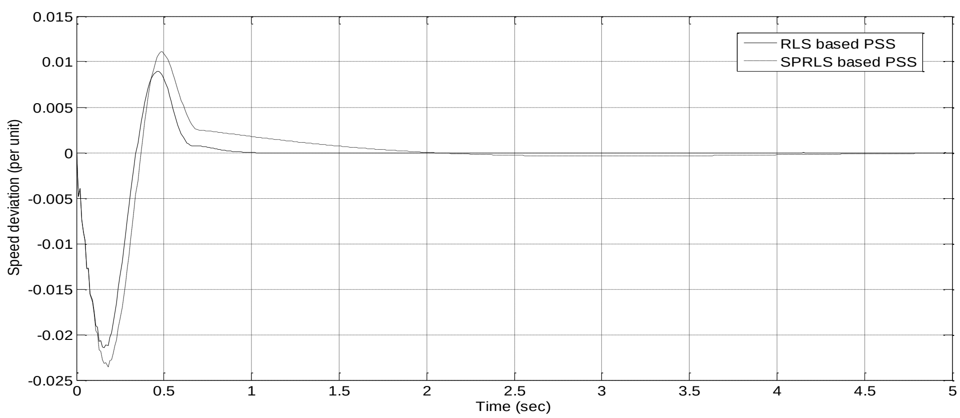


Fig. 7: Speed deviation during base load condition

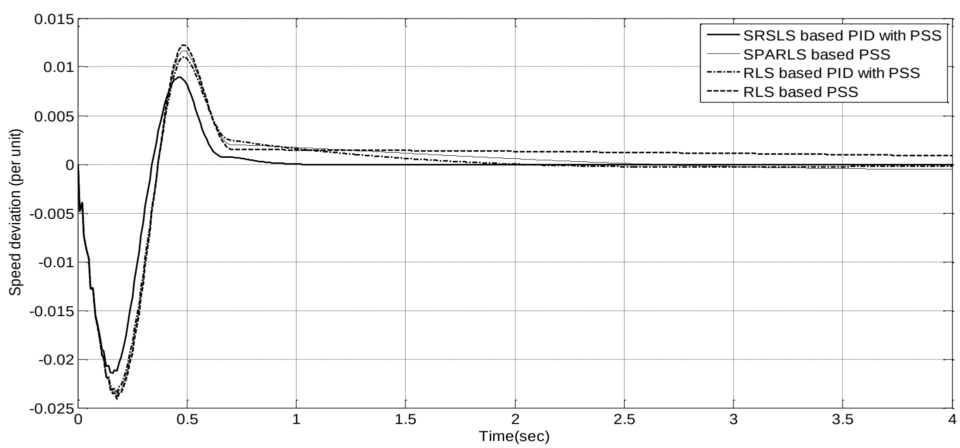

Fig. 8: Speed deviation during base load condition

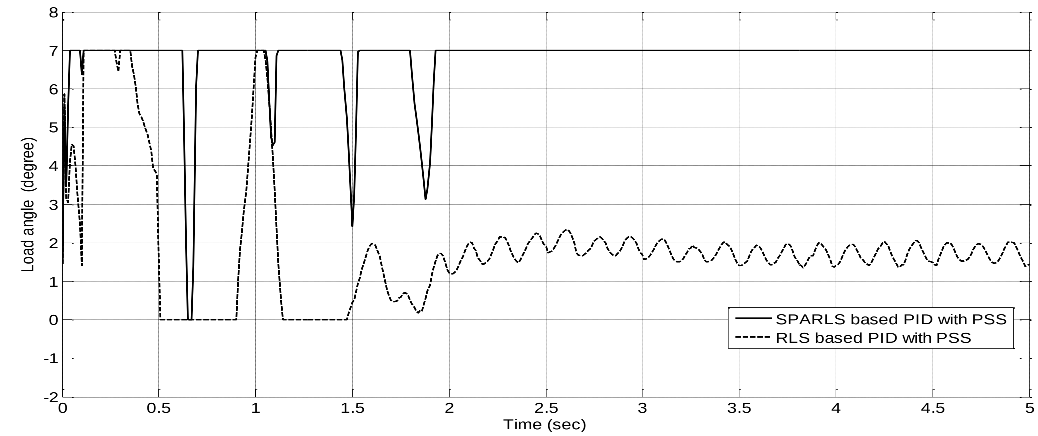


Fig. 9: Field voltage during base load condition

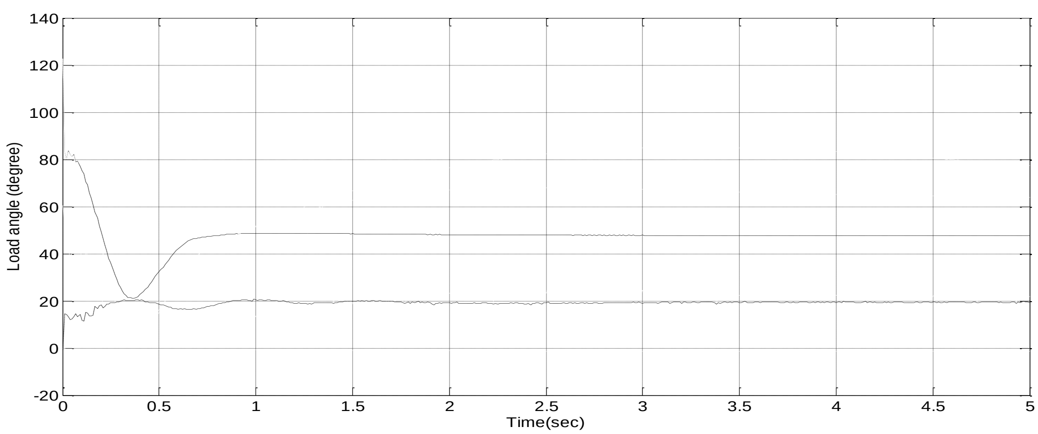


Fig. 10: Load angle during base load condition

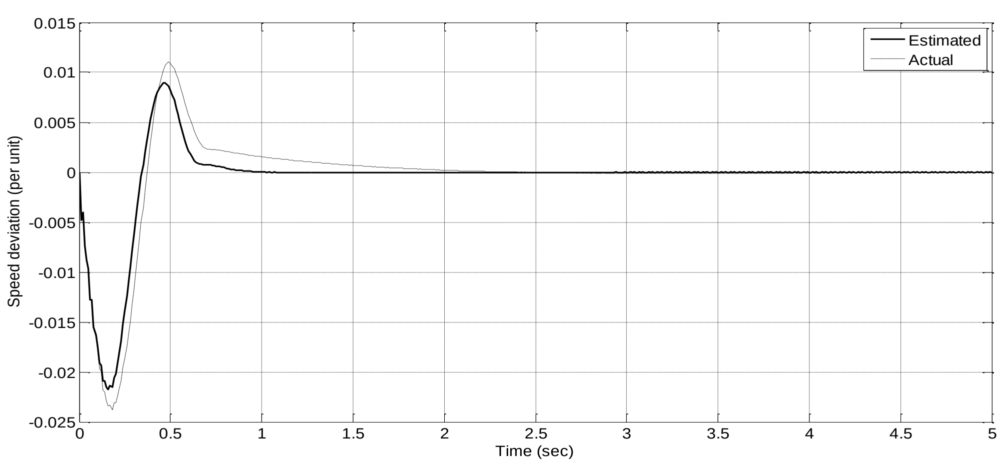


Fig. 11 (a): Performance curves for base load condition: Actual and estimated speed deviation

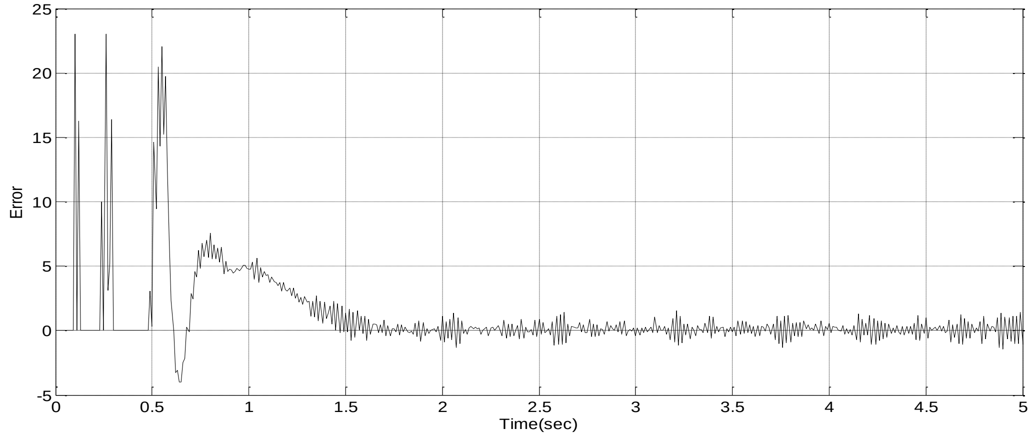


Fig. 11 (b): Performance curves for base load condition: error between actual and estimated

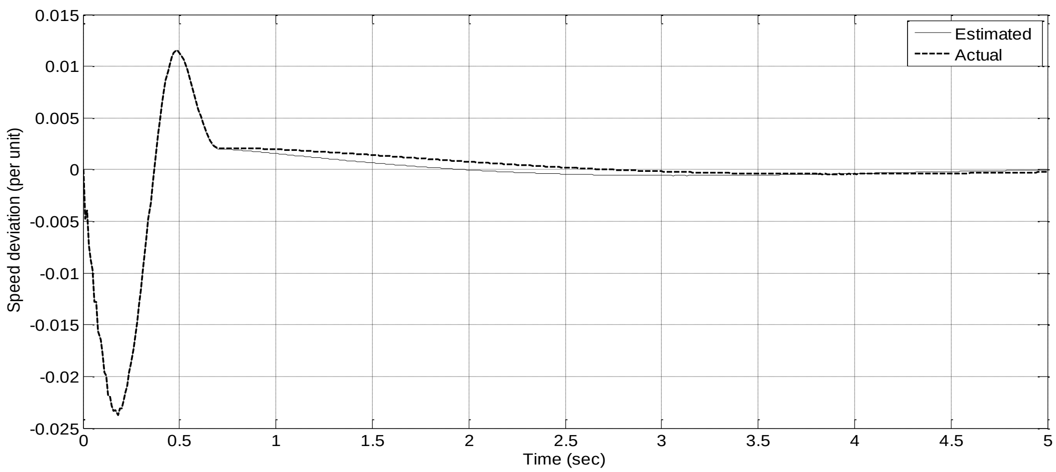


Fig. 12 (a): Performance curves for base load condition: actual and estimated speed deviation

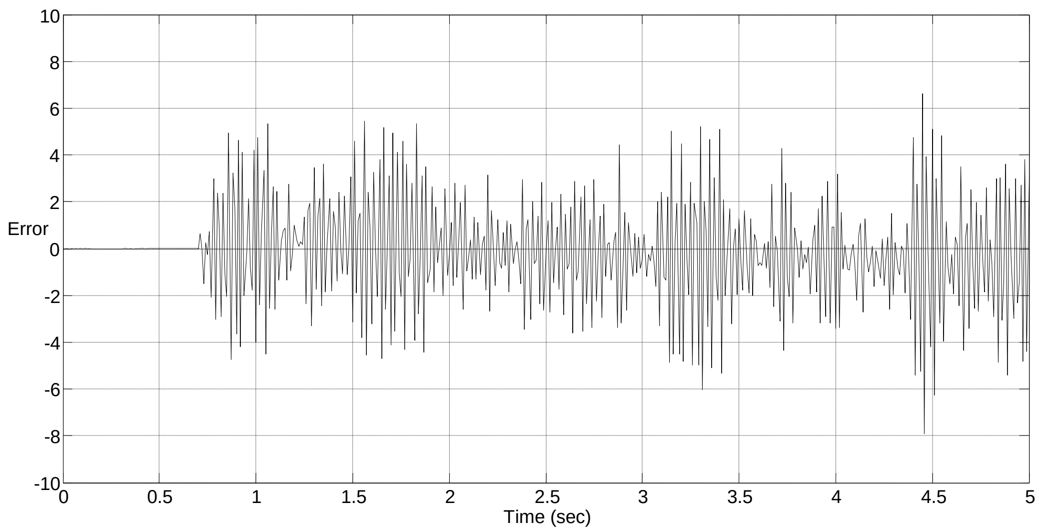


Fig. 12 (b): Performance curves for base load condition: error between actual and estimated

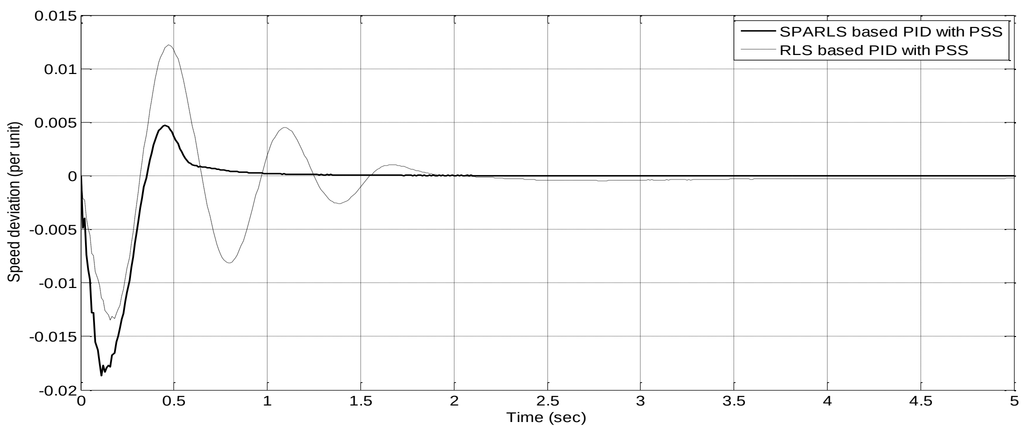


Fig. 13: Speed deviation during increasing in load condition

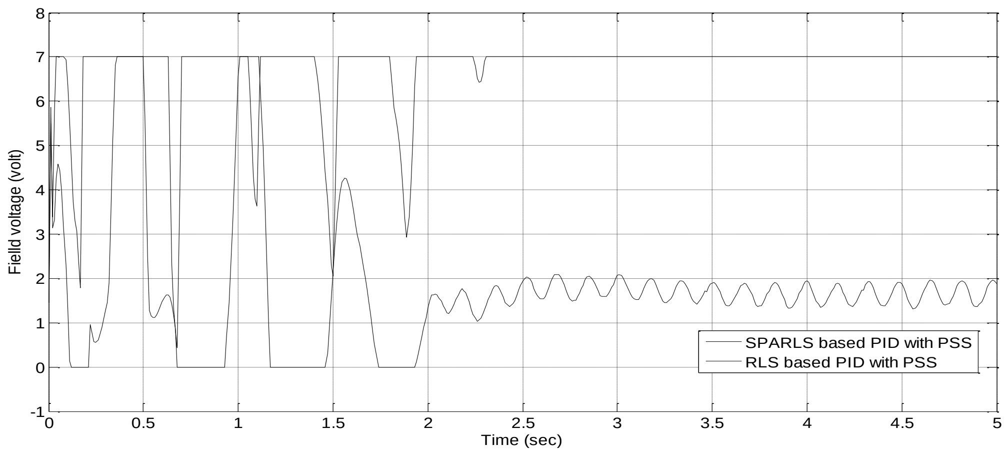


Fig. 14: Field voltage during increasing in load condition

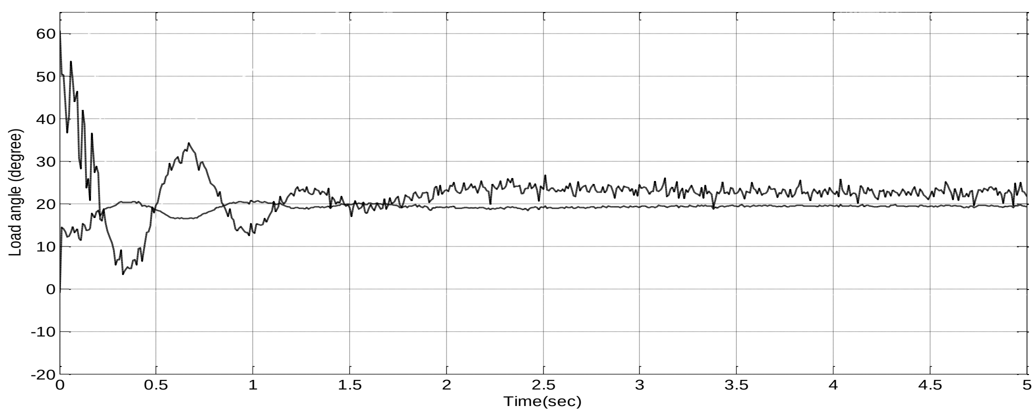


Fig. 15: Load angle during increasing in load condition

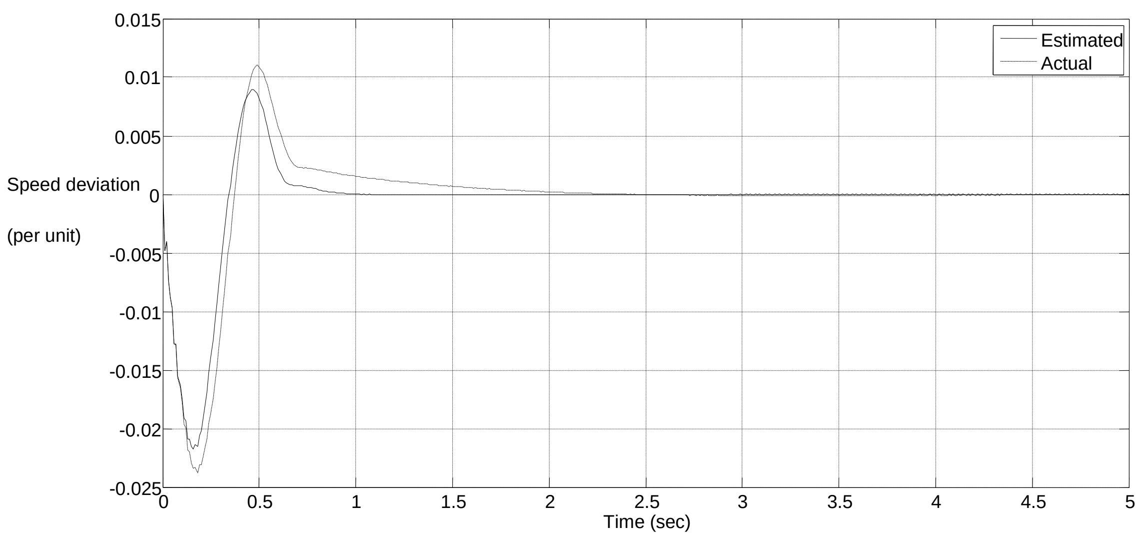

Fig. 16 (a): Performance curves for increasing in load condition: Actual and estimated speed deviation

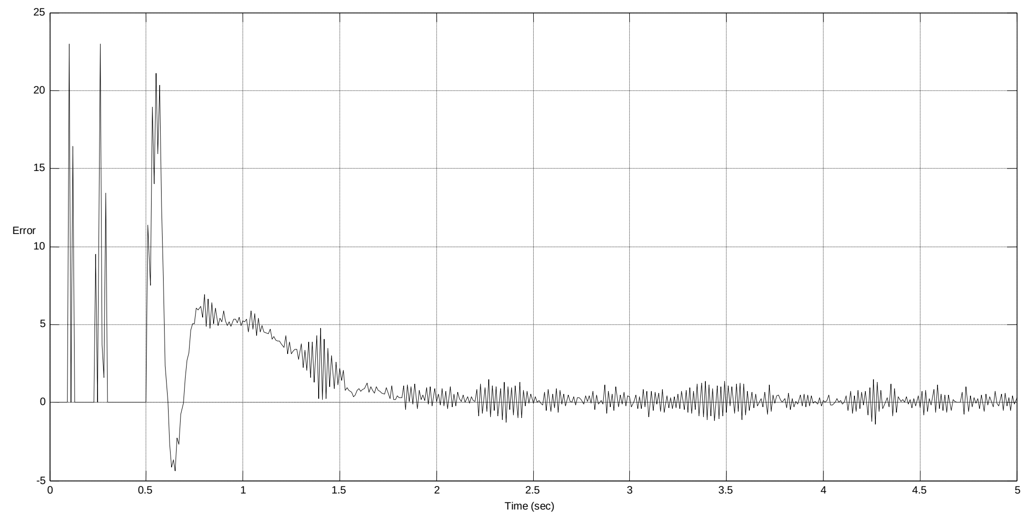


Fig. 16 (b): Performance curves for increasing in load condition: Error between actual and estimated

### 5.3 Fault Condition

This illustrates the stability of the system during vulnerable condition, three phase fault is assumed to happen at the transmission line. The fault persists in the system for 0.01 sec and it is cleared after 0.1 sec. The parameters of the system during fault condition are illustrated in Fig. 17 to Fig.18. From the Fig. 17, it is observed that the RLS based PID with PSS produced more overshoot and settles at 7 secs. The SPARLS based PID with PSS reduces the settling time to 2.5 secs and also the overshoot. According to Fig.18, the overshoot was high for RLS based PID with PSS, therefore, the stability of the system was affected. The SPARLS based PID with PSS reduces the overshoot to 50% and makes the system to reach steady state before 2.5 secs. From this case, it is inferred that PID with PSS supports the synchronous generator to maintain synchronous speed even at severe fault conditions. During the fault condition, RLS based PID with PSS cannot damp the load angle. The SPARLS based PID with PSS provides better solution by maintaining the load angle around 15 degree. However with the help of SPARLS based PID with PSS, the rotor angle is maintained at a normal level compared to SPARLS based PID with PSS.

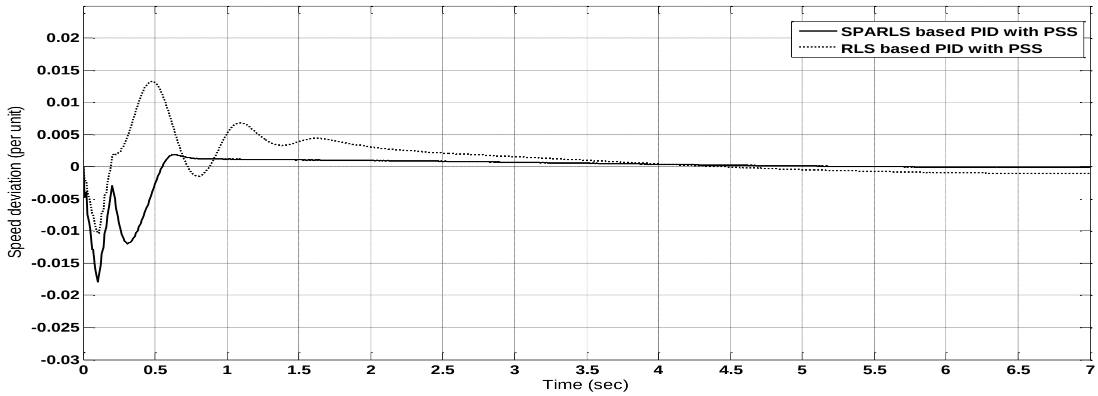


Fig. 17: Speed deviation during fault condition

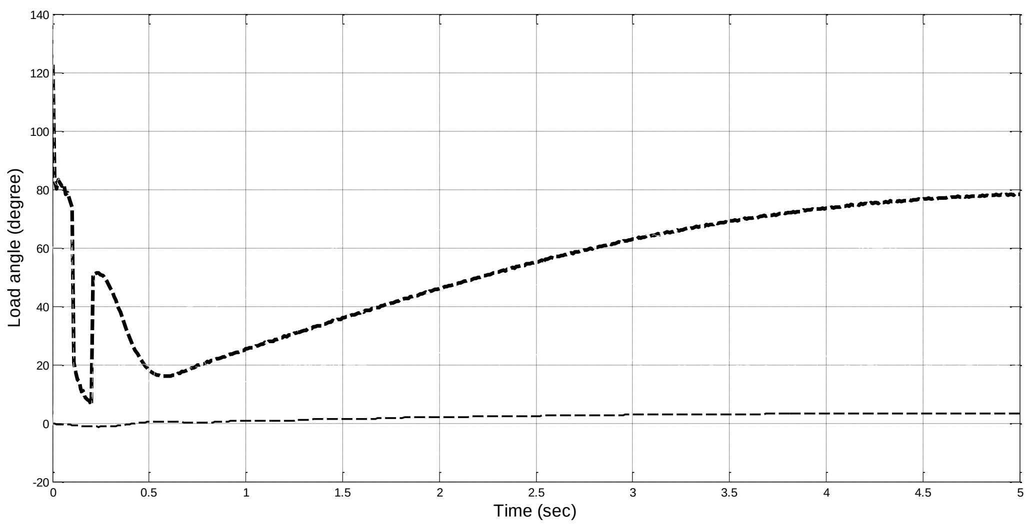


Fig. 18: Load angle during fault condition

# 6. Conclusion

This paper proposes a novel SPARLS algorithm developed for tuning of PSS based PID. The SPARLS algorithm is simple to understand and easier to design. The proposed SPARLS algorithm is developed to tune the parameter of PSS based PID and its performance is compared with RLS for the various cases such as base load, increasing in load and fault conditions. Through extensive simulations, the proposed SPARLS is shown to improve the PSS based PID parameters as compared to RLS. The proposed method is compared with the conventional RLS algorithm. The error in the speed deviation from the SPARLS algorithm under base and increasing in load condition is found to be 0.2% and 0.245 % respectively. The SPARLS algorithm is performing very well than the conventional RLS algorithm. The error in the speed deviation through the proposed SPARLS algorithm under base and increasing in load condition is found to be 0.2%. It is concluded that proposed SPARLS algorithm provides a better results, less complex and good performance than that conventional RLS algorithm over a wide operating range.

*References*

[1]. Larsen, E. V., and Swann, D. A. (1981) “Applying power system stabilizers parts I–III,” IEEE Trans. Power App. Syst., Vol. 100, No. 6, pp. 3017-3046.

[2]. M. Mary Linda, N. Kesavan Nair, (2009) “Optimal Design of Fuzzy Based Power System Stabilizer Self Tuned by Robust Search Algorithm,” Journal of Computing, Vol. 1, No. 1, pp. 44-48.
[3]. Neeraj Gupta and Sanjay K. Jain,( 2010)“Comparative Analysis of Fuzzy Power System Stabilizer Using Different Membership Functions,” International Journal of Computer and Electrical Engineering, Vol. 2, No. 2, pp. 262-267.

[4]. K. Sundareswaran and S. Razia Begum, (2004)“Genetic tuning of a power system stabilizer”, European Transactions on Electrical Power, Vol. 14, No. 3, pp 151–160.

[5]. Y. Zhang G. P. Chen 0. P. Malik G. S. Hope, (1993)“An Artificial Neural Network based Adaptive Power System Stabilizer,” IEEE Transactions on Energy Conversion, Vol. 8, No. 1,pp. 71-77.

[6]. Boonserm Changaroon, Suresh Chandra Srivastava and Dhadbanjan Thukaram, (2000) “A Neural Network Based Power System Stabilizer Suitable for On-Line Training—A Practical Case Study for EGAT System,” IEEE Transactions on Energy Conversion, Vol. 15, No. 1, pp. 103-109.
[7]. Miguel Ramirez-Gonzalez, and O. P. Malik, (2008) “Power System Stabilizer Design Using an Online Adaptive Neuro-fuzzy Controller With Adaptive Input Link Weights,” IEEE Transactions on Energy Conversion, Vol. 23, No. 3, pp. 914-922.
[8]. Ramos, R.A., Alberto, L.F.C., and Bretas, N.G, (2004)“A new methodology for the coordinated design of robust decentralized power system damping controllers,” IEEE Transactions on Power Systems, Vol. 19, No. 1, pp. 444–454.
[9]. Meng Yue, and Robert A. Schlueter, (2003)“µ-Synthesis Power System Stabilizer Design Using a Bifurcation Subsystem Based Methodology,” IEEE Transactions on Power Systems, Vol. 18, No. 4, pp. 1497-1506.
[10]. Amitava Sil, T. K. Gangopadhyay, S. Paul and A. K. Maitra, (2009)“Design of Robust Power System Stabilizer Using H Mixed Sensitivity Technique,” Third International Conference on Power Systems, Kharagpur, INDIA, December 27-29.
[11]. Ruhua You, Hassan J. Eghbali, and M. Hashem Nehrir, (2003) “An Online Adaptive Neuro- Fuzzy Power System Stabilizer for Multimachine Systems” IEEE Transactions on Energy Conversion, Vol.18, No.1, pp. 128-135.
[12]. Wenxin Liu, Ganesh K. Venayagamoorthy, and Donald C. Wunsch, (2003)“Design of an adaptive neural network based power system stabilizer,” Elsevier Science, pp. 891-899.
[13]. K.R.Sudha, Y.Butchi Raju and Prasad Reddy.P.V.G.D, (2010)“Adaptive Power System Stabilizer using support Vector Machine,” International Journal of Engineering Science and Technology, Vol. 2, No. 3, pp. 442-447.
[14]. N.M. Tabatabaei, M. Shokouhian Rad, (2010)“Designing Power System Stabilizer with PID Controller,” International Journal on Technical and Physical Problems of Engineering (IJTPE), Vol. 2, No. 3, pp. 1-7.
[15]. Sayed Mojtaba Shirvani Boroujeni, Reza Hemmati, Hamideh Delafkar and Amin Safarnezhad Boroujeni, (2011) “Optimal PID power system stabilizer tuning based on particle swarm optimization,” Indian Journal of Science and Technology, Vol. 4, No. 4, pp. 379-384.
[16]. Rabih A. Jabr, Bikash C. Pal, and Nelson Martins, (2010)“A Sequential Conic Programming Approach for the Coordinated and Robust Design of Power System Stabilizers,” IEEE Transactions on Power Systems, Vol. 25, No. 3, pp. 1627-1637.
[17]. Hasan Fayazi Boroujeni, Sayed Mojtaba Shirvani Boroujeni and Reza Hemmati, (2011)“Robust PID power system stabilizer design based on pole placement and nonlinear programming methods,” Indian Journal of Science and Technology, Vol. 4, No. 4, pp. 456-463.
[18] Soheil Ganjefar, Mojtaba Alizadeh, (2012)“On-line self-learning PID based PSS using self-recurrent wavelet neural network identifier and chaotic optimization”, COMPEL: The International Journal for Computation and Mathematics in Electrical and Electronic Engineering, Vol. 31, No. 3, pp. 1872-1891.

[19] Galotto. L, Pinto. Jo. P, Filho J. A. B and Lambect- Torres, (2008)“Recursive least square and genetic algorithm based tool for PID

controllers tuning," IEEE conference on Intelligent information technology application, Vol. 3, pp. 584-600.

[20] Daniele Angelosante, Juan Andrés Bazerque, and Georgios B. Giannakis, (2010)"Online Adaptive Estimation of Sparse Signals: Where RLS Meets the L1-Norm", IEEE Transactions on Signal Processing, Vol. 58, No. 7, pp. 3436-3447.

[21] Balwinder Singh Surjan, Ruchira Garg, (2012)"Power System Stabilizer Controller Design for SMIB Stability Study," International Journal of Engineering and Advanced Technology (IJEAT), Vol. 2, No. 1, pp. 209-214.

[22] Yuan- Yih Hsu,Kan-Lee Liou, (1987) "Design of Self-Tuning PID Power System Stabilizers for Synchronous Generators," IEEE Transactions on Energy Conversion, Vol. EC-2, No. 3,pp. 343-348.