INTRODUCTION

Power system stabilizers have been widely used to damp low frequency oscillations and to improve power system dynamic stability. The basic function of power system stabilizer is to add damping to the generator rotor oscillations by controlling its excitation using auxiliary stabilizing signals. To provide damping, the stabilizer must produce a component of electrical torque in phase with the rotor speed deviations and insufficient damping of these oscillations may limit the ability to transmit power. Power System Oscillations can be classified into two classes. The first is the oscillations associated with single generator or a single plant that is called local modes or plant modes. Local modes normally have frequencies in the range of 0.8 to 1.8 Hz [3]. The characteristics of these oscillations are well understood. They may be studied adequately, and satisfactory solutions to stability problems are developed from a system, which has detailed representation only in the vicinity of the plant. The second is the oscillations associated with groups of generators, groups of plants they are called inter area modes; Inter area modes have the frequencies in the range of 0.2 to 0.5 Hz [3]. The Characteristics of these oscillations, and the factors affecting them, are not fully understood. They are more complex to study, and to control. Estimation of dynamic stability involves two steps. The first step is to model the system, the second is to determine whether the system is stable or not. The Dynamic behavior of a power system involving synchronous generators with their controls, interconnected by networks is described by a set of nonlinear differential equations. The dynamic stability of the state is determined by the stability characteristics of the resulting set of linearized equalities. Early efforts to stabilize a machine undergoing small oscillations were somewhat random. Various signals were tried out and it was generally considered that feedback speed deviation signal into field circuit helped to damp out dynamic oscillations. It was however, realized that the speed deviation signal had to be appropriately phase advanced, in order to make up for the phase lag introduced by the exciter system. Torsional frequencies are affected when frequency deviation rather than speed deviation is used as feedback signal. According to Larsen and Swann, the speed input to the stabilizer provides the best overall local mode damping. It is essential that a stabilizer should be able to suppress local mode and inter area oscillations as effectively as possible. PSS must therefore be able to accommodate both modes. A new evolutionary computation technique, called particle swarm optimization (PSO), has been proposed and introduced recently. This technique combines social psychology principles in sociocognition human agents and evolutionary Computations. PSO has been motivated by the behavior of organisms, such as fish schooling and bird flocking. Generally, PSO is characterized as a simple concept, easy to implement, and computationally efficient. Unlike the other heuristic techniques, PSO has a flexible and well-balanced mechanism to enhance the global and local exploration abilities. In this paper, a novel PSO-based approach to PSS design is proposed. The problem of PSS design is formulated as an optimization problem with mild constraints and two different Eigen value-based objective functions. Then, a PSO algorithm is employed to solve this optimization problem. To investigate the potential of the proposed approach,
two different examples of single machine power systems have been considered.

II. PROCEDURE FOR PAPER SUBMISSION

The nonlinear equations of the system are

\[
\begin{align*}
\dot{\delta} &= \omega \dot{\omega} \\
\dot{\omega} &= \frac{1}{2H} \left( E_r \left[ X_r X_r X_r - X_q X_q X_q \right] \cos \delta \right) \\
E_r &= \frac{1}{T_E} \left( K_e E_{er} + K_v V - E_p \right)
\end{align*}
\]

The parameters of the model are function of the loading (P, Q). The state equation for the system under study is given by [2]

\[
X = AX + BU
\]

The selected regimes for designing power system stabilizer are chosen to cover heavy, medium and light loading. The proposed controller is designed based on the elected regimes. The resulting matrices of the state equation are:

1. Heavy load regime:

\[
A = \begin{bmatrix}
0 & 314 & 0 & -0.1194 & 0 \\
-0.2547 & 0 & 0.463 & 1667 \\
42.143 & 0 & -248 & 0 \\
0 & 500 & 0 & 0
\end{bmatrix},
B = \begin{bmatrix}
0 \\
0 \\
0 \\
500
\end{bmatrix},
C = [1 0 0 0]
\]

2. Normal load regime:

\[
A = \begin{bmatrix}
0 & 314 & 0 & -0.1234 & 0 \\
-0.2636 & 0 & 0.463 & 1667 \\
32.338 & 0 & -225.62 & 0 \\
0 & 500 & 0 & 0
\end{bmatrix},
B = \begin{bmatrix}
0 \\
0 \\
0 \\
500
\end{bmatrix},
C = [1 0 0 0]
\]

3. Light load regime:

\[
A = \begin{bmatrix}
0 & 314 & 0 & -0.0906 & 0 \\
-0.1934 & 0 & 0.463 & 1667 \\
-5.9319 & 0 & -255.799 & 0 \\
0 & 500 & 0 & 0
\end{bmatrix},
B = \begin{bmatrix}
0 \\
0 \\
0 \\
500
\end{bmatrix},
C = [1 0 0 0]
\]

III. MATH

A. PSS DESIGN VIA POLE PLACEMENT TECHNIQUE

In this method we assume that all state variables are measurable and are controllable. If the system considered is completely state controllable, then poles of the closed loop system may be placed at any desired locations by means of state feedback through an appropriate state feedback gain Matrix [4]. The present design technique begins with a determination of a desired closed loop poles based on the transient response and/or frequency response requirements, such as speed, damping ratio, or bandwidth, as well as steady state requirements. In this conventional approach to the design of a single input–single output control system, a controller is designed such way that the dominant closed loop poles have a desired damping ratio and an undamped natural frequency. In this approach the effects on the
response of non-dominant closed loop poles to be negligible i.e. Determination of gain matrix \((k)\) using Ackermann’s formula: The state equation for the system under study is given by \(\dot{X} = AX + BU\). Where we use the state feedback control \(u = -kx\). The use of state feedback control modifies the system equation to \(\dot{X} = (A-BK)X\). 

\[
k = [0 \ldots 0 \ 1] \{B \ A \ B \ldots \ A \}^{-1} \{D \ A \ldots \ A \} \ldots 
\]

Refer to (5) is known as Ackermann’s formula for Determination of the state feedback gain matrix [4]

**Fig2:** Step response of load angle for heavy load with 0.18P.U change in 

**Fig3:** Step response of load angle for Light load with 0.18P.U change in 

**Fig4:** Step response of load angle for Normal load with 0.18P.U change in 

### B. PSS DESIGN VIA FUZZY LOGIC CONTROLLER

In conventional control, the amount of control is determined in relation to a number of data inputs using a set of equations to express the entire control process. Expressing human experience in the form of a mathematical formula is a very difficult task, if not an impossible one. Fuzzy logic provides a simple tool to interpret this experience into reality. Fuzzy Logic is a methodology for expressing operational laws of a system in linguistic terms instead of mathematical equations.

Fuzzy logic controllers are rule-based controllers. The structure of the FLC resembles that of a knowledge based controller except that the FLC utilizes the principles of fuzzy set theory in its data representation and its logic. The basic configuration of the FLC can be simply represented in four parts [7, 8].

**Fuzzification module,** the functions of which are, first, to read, measure, and scale the control variable (e.g. speed, acceleration) and, second, to transform the measured numerical values to the corresponding linguistic (fuzzy) variables with appropriate membership values.

**Knowledge base,** which includes the definitions of the fuzzy membership functions defined for each control variable and the necessary rules that specify the control goals using linguistic variables.

**Inference mechanism,** which is the kernel of the FLC. It should be capable of simulating human decision making and influencing the control actions based on fuzzy logic. Traditional fuzzy logic approach comprises Mamdani-type and Sugeno-type inference methods. The Mamdani-type method is more intuitive and assumes the output variables as a fuzzy set [7], [8]. The Sugeno-type method expects the output variables to be singletons or dealing with consequents that are equations. So it is better suited for mathematical analysis, nonlinear system modeling and interpolation.

**Defuzzification module,** which converts the inferred decision from the linguistic variables back to numerical values. The most prevalently used methods are a) Mean of Maxima (MOM) b) Centre of Area (COA) c) Centroid method. Centroid method is used in this paper

### C. PSS DESIGN VIA PARTICLE SWARM OPTIMIZATION

Swarm behavior can be modeled with a few simple rules. Schools of fishes and swarms of birds can be modeled with such simple models. Namely, even if the behavior rules of each individual (particle) are simple, the behavior of the swarm can be complicated. Reynolds utilized the following three vectors as simple rules in the researches on boid.

1. Step away from the nearest agent
2. Go toward the destination
3. Go to the center of the swarm
The behavior of each agent inside the swarm can be modeled with simple vectors. The research results are one of the basic backgrounds of PSO. Boyd and Richerson examined the decision process of humans and developed the concept of individual learning and cultural transmission. According to their examination, people utilize two important kinds of information in decision process. The first one is their own experience; that is, they have tried the choices and know which state has been better so far, and they know how good it was. The second one is other people’s experiences; that is, they have knowledge of how the other agents around them have performed. Namely, they know which choices their neighbor have found most positive so far and how positive the best pattern of choices was. Each agent decides its decision using its own experiences and the experiences of others. The research results are also one of the basic background elements of PSO.

Basic Particle Swarm Optimization
According to the above background of PSO, Kennedy and Eberhart developed PSO through simulation of bird flocking in a two-dimensional space. The position of each particle is represented by its x, y axis position and also its velocity is expressed by \( v_x \) (the velocity of x axis) and \( v_y \) (the velocity of y axis). Each agent knows its best value so far \( P_{best} \) and its x, y position. This information is an analogy of the personal experiences of each agent. Moreover, each agent knows the best value so far in the group \( g_{best} \) among \( P_{best} \)’s. This information is an analogy of the knowledge of how the other agents around them have performed. Each particle tries to modify its position using the following information:
The current positions \((x, y)\),
The current velocities \((v_x, v_y)\),
The distance between the current position \(P_{best}\) and

This modification can be represented by the concept of velocity (modified value for the current positions). Equation of each particle can be modified by the following equation:

\[
v^{t+1}_x = v^t_x + \frac{\text{rand}_1 \times (P_{best} - s^t_x) + \text{rand}_2 \times (g_{best} - s^t_x)}{\text{iter}}\]

(5)

where \( s^t_x \) is velocity of particle \( i \) at iteration \( t \), \( w \) is inertia weight, \( C_1 \) and \( C_2 \) is random coefficients, \( \text{rand}_1 \) and \( \text{rand}_2 \) are random number between 0 and 1, \( s^t_x \) is current position of particle \( i \) at iteration \( t \), \( P_{best} \) is \( P_{best} \) of particle \( i \), and \( g_{best} \) is best of the group.

The following weighting function is usually utilized

\[
w = \frac{\text{iter} \times \text{iter}_{max}}{\text{iter}_{max}}\]

(6)

Where \( w_{max} \) is initial weight, \( w_{min} \) is final weight, \( \text{iter}_{max} \) is maximum iteration number, \( \text{iter} \) and is current iteration number. The meanings of the right-hand side (RHS) of (5) can be explained as follows. The RHS of (5) consists of three terms (vectors). The first term is the previous velocity of the particle. The second and third terms are utilized to change the velocity of the particle. Without the second and third terms, the particle will keep on “flying” in the same direction until it hits the boundary. Namely, it tries to explore new areas and, therefore, the first term corresponds with diversification in the search procedure. On the other hand, without the first term, the velocity of the “flying” particle is only determined by using its current position and its best positions in history. Namely, the particles will try to converge to their \( P_{best} \)’s and/or \( g_{best} \) in terms correspond with intensification in the search procedure. The current position (searching point in the solution space) can be modified by the following equation:

\[
s^{t+1} = s^t + v^{t+1} \]

(7)

Fig 5. Concept of Modification of a Searching Point by PSO

The General PSO Algorithm
Step 1: Generation of initial condition of each particle. Initial searching points \( s^0 \) and velocities \( v^0 \) of each particle are usually generated randomly within the allowable range. The current searching point is \( s^0 \) to for each particle. The best evaluated value of \( P_{best} \) is set to \( g_{best} \), and the particle index number with the best value is stored.

Step 2: Evaluation of searching point of each particle. The objective function value is calculated for each particle. If the value is better than the current \( P_{best} \) of the particle, the \( g_{best} \) value is replaced by the current value. If the best value of \( P_{best} \) is better than the current, \( g_{best} \) is replaced by the best value and the particle index number with the best value is stored.

Step 3: Modification of each searching point. The current searching point of each particle is changed using (5), (6), and (7).

Step 4: Checking the exit condition. The current iteration number reaches the predetermined maximum iteration number, then exits. Otherwise, the process proceeds to step 2.
IV. CONTROL SCHEME

A) Using Fuzzy controller:

In this controller, the Rotor speed deviation and the derivative of rotor speed deviation are selected as inputs and the supplementary stabilizing signal is the output of the controller. The parameters of the controller should be determined by trial and error, using the simulation of system. Five fuzzy subsets have been used in this scheme. For each of these fuzzy sets, triangular membership functions (TMF), Gaussian membership function (GMF) and trapezoidal membership functions (TZMF) have been used. The triangular membership functions with range of each variable and degree are shown in below. Fuzzy subsets results through these fuzzy subsets for computing the output is shown in table 1.

Step Response of Load Angle Deviation Δδ, for heavy, Normal, and light load conditions: The dynamic behavior of the system with fuzzy PSS and Without power system stabilizer is shown in Fig.8-10 for different membership functions. From these figures it can be seen that the oscillations of the variables are more quickly damped in fuzzy logic power system stabilize with Triangular membership functions as compared to Gaussian and Trapezoidal membership Functions. The performance of power system stabilizers designed Using conventional pole-placement technique and fuzzy Logic controller is depicted in Fig.10-15.

![Fig.6: General Flowchart of PSO](image6.png)

![Fig.7: Triangular membership function of speed deviation (ω)](image7.png)

![Fig.8: Triangular membership function of derivative of Speed Deviation (dω)](image8.png)

![Fig.9: Triangular membership function of derivative of Speed Deviation (dω)](image9.png)

![Step Response of Load Angle Deviation Δδ, for heavy, Normal, and light load conditions](image10.png)
B) Using particle swarm optimization (PSO)

The problem of choosing the parameters of power system stabilizer designed using lead controller for a single machine connected to an infinite bus system is converted to an optimization problem and it can be solved using Particle Swarm Optimization. An eigenvalue based objective function is derived to improve the system damping and thereby improving the system rotor angle stability [8].

Maximize = Minimum (ξ \times \text{damping of electromechanical modes}) ... (8)

The parameters of lead controller PSS are:
- $K_{PSS}$: Power System Stabilizer gain
- $T_1$: Lead time constant in seconds
- $T_2$: Lag time constant in seconds

Damping is maximized subject to following constraints:

$$
\begin{align*}
K_{PSS}^\text{min} & \leq K_{PSS} \leq K_{PSS}^\text{max} \\
T_1^\text{min} & \leq T_1 \leq T_1^\text{max} \\
T_2^\text{min} & \leq T_2 \leq T_2^\text{max}
\end{align*}
$$

PSO Algorithm for PSS Design:

Step 1: Set the time counter $t=0$ and generate ‘$n$’ particles (population) randomly within the allowable range

$$\text{Particle}_j(0) = [x_{1j}(0), x_{2j}(0), x_{3j}(0), \ldots, x_{mj}(0)]$$

Where, $x_{ij}(0)$ is generated randomly by choosing a value with uniform probability over the $i^{th}$ optimized parameter in the search space as $[x_{ij}^\text{min}, x_{ij}^\text{max}]$ and ‘$n$’ is the number of optimized parameters. And finally population is represented as ‘POP’.

$$\text{POP}(0) = [x_{1j}(0), x_{2j}(0), x_{3j}(0), \ldots, x_{nj}(0)]$$

The particle for this problem is, particle = [PSS $T_1$ $T_2$]

Step 2: And similarly generate randomly, the initial velocities within the allowable range using the equation given below.

$$v_{i,j}^\text{max} = \frac{x_{i,j}^\text{max} - x_{i,j}^\text{min}}{N}$$

$$\text{velocity}_j(0) = [v_{1j}(0), v_{2j}(0), \ldots, v_{nj}(0)]$$

Where, $v_{ij}(0)$ is generated randomly by choosing a value with uniform probability over the $i^{th}$ optimized parameter in the search space as $[-v_{ij}^\text{max}, v_{ij}^\text{max}]$. Set initial inertia weight $w(0)$.

Step 3: Evaluate the objective function $J$ for each particle in the initial population ‘POP’, and set this particle as $P_{best}$ (known as individual best). And search for the best value of objective function $J_{best}$. Set the particle associated $J_{best}$ as $G_{best}$.

Step 4: Update the timer counter $t=t+1$, and update the inertia weight ‘$w$’ using the following equation.

$$w = w_{\text{max}} - \frac{iter_{\text{max}}}{\text{iter}} \times \text{iter}$$

Step 5: Velocity updating, using $G_{best}$ and $P_{best}$, the velocity of each particle can be modified by the following equation.

$$v_{i,j}^{t+1} = w v_{i,j}^t + C_1 r_1 \times (P_{best} - x_i^t) + C_2 r_2 \times (G_{best} - x_i^t)$$
Each particle changes its position using the following equation
\[ P_{t+1} = s_{t+1} = s_t^e + v_t^e \]

Step 6: Evaluate the objective function \( J(t + 1) \) for each particle in the \( P_{t+1} \). If this value is greater than the value evaluated in previous iteration then replace \( v_{	ext{best}} \) as current particle \( J(t+1) \).

Step 7: Search for the better value among \( J(t+1) \) and if this value is greater than then \( P_{t+1} \) replace \( P_{t+1} \) as particle associated with \( J(t+1) \) and \( v_{	ext{best}} \) as \( J(t+1) \).

Step 8: Checking the exit condition. If the current iteration number reaches the predetermined maximum iteration number, then exits. Otherwise, the process proceeds to step 3.

V. SIMULATION RESULTS

The parameters of the CPSS are tuned using Particle Swarm Optimization by maximizing the objective function given by Eqn. (6.4). Table 6.1 shows the parameters of PSO which provides best results (Optimal results).

<table>
<thead>
<tr>
<th>PSO Parameters</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of Particles</td>
<td>30</td>
</tr>
<tr>
<td>Particle dimension</td>
<td>3</td>
</tr>
<tr>
<td>Weighing coefficients C1 and C2</td>
<td>2</td>
</tr>
<tr>
<td>( W_{\text{min}} ) and ( W_{\text{max}} )</td>
<td>0.4 and 0.9</td>
</tr>
<tr>
<td>Maximum Number of iterations</td>
<td>50</td>
</tr>
</tbody>
</table>

Fig 16: Rotor Angle deviation due to 0.2 step change in \( V_{\text{ref}} \) for the operating point 1.2+0.2j

Fig 17: Rotor Angle deviation due to 0.2 step change in \( V_{\text{ref}} \) for the operating point 1.0+0.0j

Fig 18: Rotor Angle deviation due to 0.2 step change in \( V_{\text{ref}} \) for the operating point 0.7+0.3j

Fig 19: Rotor Angle deviation due to 0.2 step change in \( V_{\text{ref}} \) for the operating point 0.4+0.1j

Fig 20: Rotor Angle deviation due to 0.2 step change in \( V_{\text{ref}} \) for the operating point 1.1+0.1j

Fig 21: Rotor Angle deviation due to 0.2 step change in \( V_{\text{ref}} \) for the operating point 0.8+0.2j
CONCLUSIONS

In this paper, power system stabilizer based on and fuzzy logic controllers and PSO (particle swarm optimization) have been developed for a single machine connected to an infinite bus system. Besides ensuring system stability, the proposed fuzzy logic controller and PSO (particle swarm optimization) provides a minimum overshoot and damping response over a wide range of power system operating conditions as compared to conventional PSS based on mathematical model. The CPSS designed to provide optimal performance at an operating point cannot be expected to give the same performance at other operating points. Hence the parameters of conventional power system stabilizer need to be returned every time the operating condition of power system changes, so that it continuous to provide desired performance, but this would not be the case in fuzzy controller. Moreover that the design of the fuzzy controller requires no mathematical model of generator and power system as would be needed by the conventional power system stabilizers (CPSS).

REFERENCES


A. Equations

The k-parameters of the machine expressed in terms of P and Q:

\[ K_1 = C_2 \times \frac{P}{(P^2 + (Q + C_f^2))} + Q + C_1 \]

\[ K_2 = C_4 \times \frac{P}{\sqrt{P^2 + (Q + C_f^2)}} \]

\[ K_3 = \frac{P}{x_d^2 + x_e^2} \]

\[ K_4 = \frac{P}{x_d^2 + x_e^2} \]

\[ K_5 = C_7 \times \frac{P}{(P^2 + (Q + C_f^2))} \]

\[ K_6 = C_7 \times \frac{P}{\sqrt{P^2 + (Q + C_f^2)}} \]

\[ C_1 = \frac{x_d + x_e}{x_d + x_e} \]

\[ C_2 = \frac{x_d + x_e}{x_d + x_e} \]

\[ C_3 = \frac{x_d - x_e}{x_d + x_e} \]

\[ C_4 = \frac{V}{x_d + x_e} \]

\[ C_5 = \frac{x_d - x_e}{x_d + x_e} \]

\[ C_6 = C_1 \times (x_d - x_e) \]

\[ C_7 = \frac{x_d}{x_d + x_e} \]

B. List of Symbols

All quantities are in p.u. except the time constants and M are in seconds.

\( \tau_m \): Mechanical Torque.

\( \tau_e \): Electrical Torque.

\( V_T \): Terminal Voltage.

\( E_{d} \): Induced Emf Proportional To Field Current.

\( E_{Q} \): Generator Field Voltage.

\( V_{ref} \): Reference Value of Generator Field Voltage.

\( x_d, x_q \) : Generator Direct-Axis Transient Reactance, Direct and Quadrature-Axis Synchronous Reactance Respectively.

\( x_s \) : External (Line) Reactance

\( \varepsilon \) : Angle between quadrature axis and infinite busbar.

\( \Delta \omega \) : Speed Deviation.

\( \omega_{ns} = 2\pi f, f = 50 \text{ Hz} \)

\( T_{ds} \): Open circuit direct axis transient time constant.

\( M \) : Inertia coefficient.

\( K_G, T_E \) : Exciter Gain and Time Constant.

\( U \) : Stabilizing Signal (PSS output).

\( V \) : infinite busbar voltage.

\( P, Q \) : Real and Reactive Power Loading

\( K_1 - K_4 \) : The k-parameters of the synchronous generator block diagram.