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Implementing the Henry Gas Solubility Optimization Algorithm for Optimal Power System Stabilizer Design

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ABSTRACT

This study assesses the feasibility of the Henry gas solubility optimization (HGSO), a recent novel metaheuristic algorithm, to achieve optimal parameters for a power system stabilizer (PSS) employed in a power system. To do so, the design problem was defined as an optimization problem and an integral of time-multiplied absolute error objective function was adopted. This objective function was minimized to tune the PSS parameters and improve the dynamic performance of the power system. The performance was evaluated using a single-machine infinite-bus system, and the obtained results were compared with atom search optimization and conventional based designed systems. The proposed HGSO approach for tuning PSS parameters has been shown to suppress electromechanical oscillations and provide a better statistical performance and convergence ratio.
Keywords: Damping oscillations, dynamic stability, Henry gas solubility optimization, power system stabilizer

Introduction

Poorly damped oscillations are undesirable for power grid operation because they threaten the security and integrity of the grid. This is particularly crucial for current power grids because power system interconnections tend to grow. In addition, the expected lifetime of power system machines may also decrease in such cases. A small disturbance may cause the collapse of the entire system if it is not appropriately treated, and this could lead to interruption of power supply and result in financial loss. If a system is not damped adequately, low-frequency oscillations generate oscillatory instability and cause system separation. Therefore, damping a power system is crucial in terms of enhancing its power transfer capability and stabilizing it. The latter requires small signal stability because it is characterized by low-frequency oscillations. In general, small signal stability is enhanced and the performance of single-machine infinite-bus (SMIB) and multi-machine power systems damped using a power system stabilizer (PSS). Using a PSS helps compensate for the phase lag error between the exciter input and the electrical torque and generates a torque component on the rotor [1, 2].

Despite the nonlinear structure of power systems in general, the design of a conventional PSS relies on linear control theory. This technique considers a linearized model of a power system. The parameters and structure of PSS are regulated to achieve the best performance around a nominal operating point. As noted above, the operating conditions of a power system can fluctuate consistently over a wide range because of their nonlinear nature. In addition, the configuration of a power system changes over time, which requires the adjustment of PSS parameters to maintain performance. Therefore, achieving an optimum performance for the entire operating condition is not feasible using conventional PSSs including fixed parameters. Alternative control techniques are available for PSS design, including feedback linearization, self-tuning regulators, and pole placement and shifting. However, intensive computations and long computer processing time are considerable disadvantages of those techniques [3].

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For both SMIB and multi-machine power systems, several metaheuristic techniques have recently been suggested as ways to handle offline tuning of PSS parameters by considering a wide range of operating conditions. Some of those techniques include harmony search [4], artificial bee colony [5], cuckoo search [6], biogeography-based optimization [7], bat [8], salp swarm [9], firefly [10], kidney-inspired [3], improved whale optimization [11], particle swarm optimization [12], and farmland fertility [13] algorithms. The main advantage of employing such techniques is the ability to explore optimal or near-optimal solutions of the optimization problem because they have derivative-free structures.

The Henry gas solubility optimization (HGSO) algorithm is a recent metaheuristic search algorithms proposed to solve complex optimization problems [14]. HGSO has already been adopted in several applications, such as tackling issues related to maximum power point tracking techniques [15], enhancing classification accuracy in feature selection [16], predicting parameters of support vector regression [17], and designing proportional integral derivative (PID) [18] and fractional order PID [19] controllers for direct current motor speed regulation and automatic voltage regulator control, respectively. However, there are still many real-world engineering problems that can be used to evaluate the performance of HGSO. Therefore, this study assesses the performance of this novel algorithm for a new engineering problem by investigating the applicability of HGSO for effective PSS design in a SMIB system for the first time.

The research was conducted by formulating the design of the suggested PSS damping controller as an optimization problem, and the HGSO algorithm was used to search for optimal controller parameters. The stability performance of the SMIB system was improved by minimizing the integral of time multiplied absolute error (ITAE) as an objective function. Eigenvalue analysis and the results of nonlinear time domain simulation show the effectiveness of the proposed controller in terms of providing good damping characteristics to system oscillations. In addition, the superiority of the proposed method was also validated for PSS tuning via comparisons with conventional and no controller cases and an atom search optimization (ASO) algorithm–based controller.

Henry Gas Solubility Optimization

HGSO is a recently proposed global optimization approach based on Henry's law of gas solubility [14]. This law explains the solubility of gases in a fluid. The mathematical modeling of this optimization technique can be represented in the following steps.

Initialization

The following equation is used to randomly initialize the search using *N* gas particles.

$$X_i(t+1) = X_{min} + r \times (X_{max} - X_{min}) \quad (1)$$

In (1), X_i denotes the position of the *i*th particle, *r* represents a number within [0,1] and randomly generated, *t* is the iteration number, and X_{min} is the lower bound of the search space and X_{max} is the upper bound. $j(H_j(t))$, $P_{i,j}$, and $j(C_j)$ represent Henry's constant, the partial pressure, and a constant value of each gas particle in *j*th cluster, respectively. The latter terms are initialized using (2)–(4) below, where constant values of l_1, l_2, and l_3 are equal to 5×10^{-2}, 100, and 10^{-2}, respectively.

$$H_j(t) = l_1 \times rand(0,1) \quad (2)$$

$$P_{i,j} = l_2 \times rand(0,1) \quad (3)$$

$$C_j = l_3 \times rand(0,1) \quad (4)$$

Clustering

The population is split into *k* clusters owing to the different types of gases available in HGSO. Those gas types have different values of Henry's constant, H_j.

Evaluation of Fitness

The objective function considered is used to evaluate ith gas particle in *j*th cluster. The population is ranked after the evaluation process using fitness values. The latter helps find the best particle of both each cluster ($X_{i,j}$) and the entire population (X_{best}).

Updating Henry's Coefficient

In each iteration, Henry's coefficient is updated for *j*th cluster using (5):

$$H_j(t+1) = H_j(t) \times e^{(-C_j \times (1/T(t) - 1/T^{\theta}))}, T(t) = e^{(-t/tm)}, T^{\theta} = 298.15 \quad (5)$$

where maximum iterations and temperature values are represented by *tm* and *T*, respectively.

Updating Solubility

The solubility of *i*th gas in cluster *j* is denoted by $S_{i,j}$. This parameter is updated using (6):

$$S_{i,j}(t) = K \times H_j(t+1) \times P_{i,j}(t) \quad (6)$$

where *K* and $P_{i,j}$ are a constant and the partial pressure, respectively. These are user-defined values and equal to 1 by default.

Updating Position

The position $X_{i,j}$ in iteration of *t*+1 is updated using (7):

$$X_{i,j}(t+1) = X_{i,j}(t) + F \times r_1 \times \gamma \times \left(X_{i,best}(t) - X_{i,j}(t)\right) + F \times r_2 \times \alpha \times \left(S_{i,j}(t) \times X_{best}(t) - X_{i,j}(t)\right),$$
$$\gamma = \beta \times e^{-\left(\frac{F_{best}(t)+\varepsilon}{F_{i,j}(t)+\varepsilon}\right)} \; and \; \varepsilon = 0.05 \quad (7)$$

where two different randomly generated values between [0, 1] are represented by r_1 and r_2. Controlling the direction of the search is denoted by *F* flag, whereas β is a user-defined constant and has a default value of 1. γ represents the ability of the search agent to interact with the search agents in its cluster; the influence of the other search agents on search agent *i* is denoted by α. The best candidate solution in *j*th cluster is denoted by $X_{j,best}$, whereas the best solution in the entire population is shown by X_{best}.

Escaping from Local Optimum

The HGSO algorithm reinitializes the worst candidate solutions (N_w) as an effective strategy to escape from the local minimum. The worst candidates are selected using (8) and then reinitialized using (1):

$$N_w = N \times (rand(c_2 - c_1) + c_1), c_1 = 0.1 \ and \ c_2 = 0.2 \tag{8}$$

where population size is represented by N and c_1 and c_2 are used as constants for providing the ratio of the worst agents in the population. The Henry gas solubility principle can briefly be summarized as the volume of the gas decreasing with increasing pressure in an equilibrium state. This principle can clearly be observed from Figure 1.

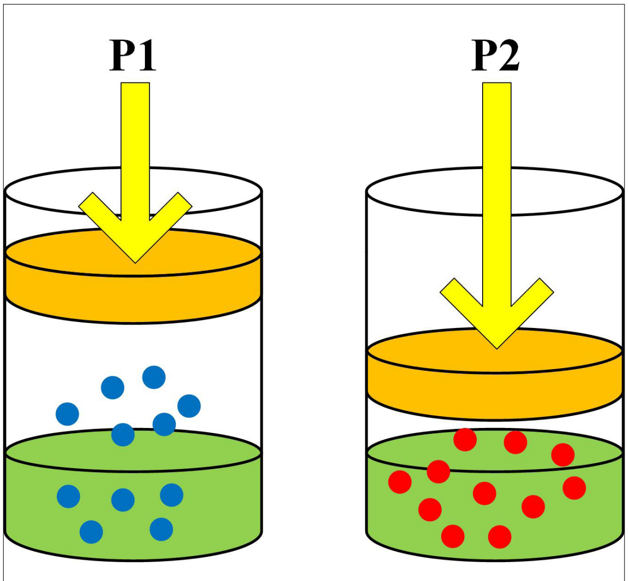

Figure 1. Henry gas solubility principle [14]

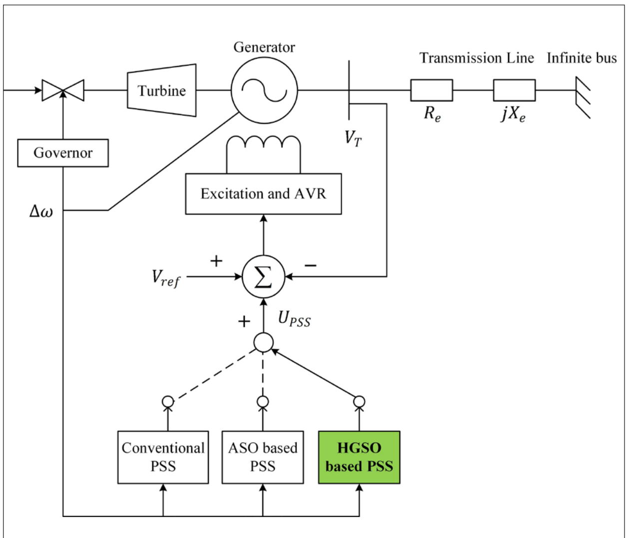

Figure 2. SMIB power system with PSS.
PSS, power system stabilizer; SMIB, single-machine infinite-bus

Formulating the Problem

Power system model

This study considered a power system consisting of SMIB through a transmission line, as shown in Figure 2. The machine was assumed to be equipped with a fast exciter. A PSS was integrated with this system to improve small signal oscillations. The fourth-order model of the SMIB power system can be given as follows [2, 20]:

$$\dot{\delta} = \omega_0(\omega - 1) \tag{9}$$

$$\dot{\omega} = [P_m - P_e - D(\omega - 1)]/M \tag{10}$$

$$\dot{E}'_q = \left[E_{fd} - E'_q - (x_d - x'_d)i_d\right]/T'_{d0} \tag{11}$$

$$\dot{E}_{fd} = \left[K_A(V_{ref} - V_T + U_{PSS}) - E_{fd}\right]/T_A \tag{12}$$

$$P_e = E'_q i_q + (x_q - x'_d)i_d i_q \tag{13}$$

Structure of a Single-Machine Infinite-Bus (SMIB) System with a Power System Stabilizer (PSS) Controller

A PSS is a lead-lag compensator that produces a component of electric torque to damp generator rotor oscillations by controlling its excitation. The basic block diagram of a speed input single-stage PSS, which acts through excitation system, is depicted in Figure 3. The transfer function of widely used PSS is given as follows [2]:

$$U_{PSS} = K_{PSS}\left(\frac{sT_W}{1 + sT_W}\right)\left(\frac{1 + sT_1}{1 + sT_2}\right)\Delta\omega \tag{14}$$

The synchronous speed deviation signal (Δω) is the input signal provided to the PSS and the output is the stabilizing signal (U_{PSS}). This type of PSS consists of the stabilizer gain, washout filter, lead-lag structured phase compensation, and limiter.

Linearized Model of a SMIB System with a PSS Controller

The linearized Heffron–Phillips model of the SMIB system, including PSS dynamics, can be represented using the following state space equations by neglecting washout filter stage [2, 20]:

$$\Delta\dot{\delta} = \omega_0\Delta\omega \tag{15}$$

$$\Delta\dot{\omega} = -\frac{K_1}{M}\Delta\delta - \frac{D}{M}\Delta\omega - \frac{K_2}{M}\Delta E'_q \tag{16}$$

$$\Delta\dot{E}'_q = -\frac{K_4}{T'_{d0}}\Delta\delta - \frac{1}{K_3 T'_{d0}}\Delta E'_q + \frac{1}{T'_{d0}}\Delta E_{fd} \tag{17}$$

$$\Delta\dot{E}_{fd} = -\frac{K_A K_5}{T_A}\Delta\delta - \frac{K_A K_6}{T_A}\Delta E'_q - \frac{1}{T_A}\Delta E_{fd} + \frac{K_A}{T_A}\Delta U_{PSS} \tag{18}$$

$$\Delta\dot{U}_{PSS} = -\frac{K_{PSS}T_1}{T_2}\frac{K_1}{M}\Delta\delta + \left(\frac{K_{PSS}}{T_2} - \frac{K_{PSS}T_1}{T_2}\frac{D}{M}\right)\Delta\omega - \frac{K_{PSS}T_1}{T_2}\frac{K_2}{M}\Delta E'_q - \frac{1}{T_2}\Delta U_{PSS} \tag{19}$$

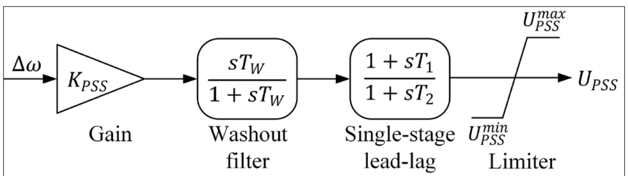

Figure 3. Block diagram of single-stage lead-lag PSS controller.
PSS, power system stabilizer

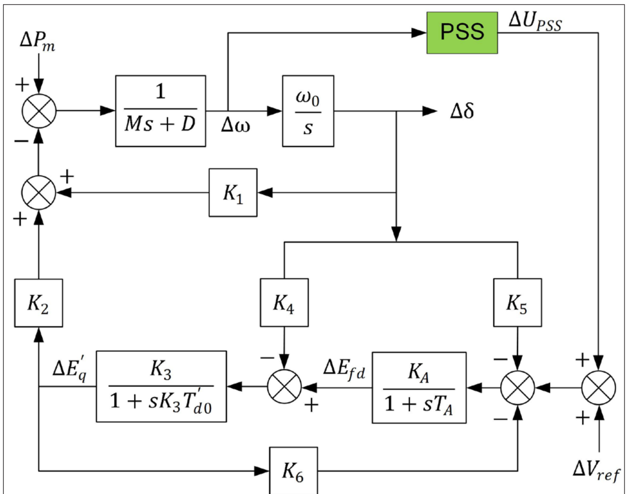

Figure 4. Representation of the Heffron–Phillips model with PSS controller.
PSS, power system stabilizer

Here, (19) is added to general equations (15)–(18) of the SMIB system because of the installation of a PSS. The system matrix (A_{PSS}) of this combined model was presented in (20). The system matrix without PSS can be easily obtained by excluding the PSS output state (U_{PSS}).

$$A_{PSS}=\begin{bmatrix} 0 & 2\pi f & 0 & 0 & 0 \\ -\frac{K_1}{M} & -\frac{D}{M} & -\frac{K_2}{M} & 0 & 0 \\ -\frac{K_4}{T'_{d0}} & 0 & -\frac{1}{K_3 T'_{d0}} & \frac{1}{T'_{d0}} & 0 \\ -\frac{K_A K_5}{T_A} & 0 & -\frac{K_A K_6}{T_A} & -\frac{1}{T_A} & \frac{K_A}{T_A} \\ -\frac{K_{PSS} T_1}{T_2}\frac{K_1}{M} & \left(\frac{K_{PSS}}{T_2}-\frac{K_{PSS} T_1}{T_2}\frac{D}{M}\right) & -\frac{K_{PSS} T_1}{T_2}\frac{K_2}{M} & 0 & -\frac{1}{T_2} \end{bmatrix} \quad (20)$$

In this study, the state vector is given as $\Delta x=[\Delta\delta\ \Delta\omega\ \Delta E'_q\ \Delta E_{fd}\ \Delta U_{PSS}]^T$. The linearized dynamic model of a SMIB power system with PSS controller is represented in Figure 4.

Objective Function and Tuning PSS Parameters Using Henry Gas Solubility Optimization HGSO

It is feasible to choose the parameters of the PSS to minimize the objective function provided in [21]. This performance index is based on ITAE and given below:

$$ITAE=\int_0^{T_{sim}} t\cdot|\Delta\omega(t)|\cdot dt \quad (21)$$

where $\Delta\omega(t)$ is the rotor speed deviation following a severe disturbance and T_{sim} is simulation time. The advantage of this index is the requirement of minimal dynamic plant information. Minimizing the ITAE objective function using the parameters given in Table 1 is subjected to the following boundaries:

$$\begin{aligned} K_{PSS}^{min} &\le K_{PSS} \le K_{PSS}^{max} \\ T_1^{min} &\le T_1 \le T_1^{max} \\ T_2^{min} &\le T_2 \le T_2^{max} \end{aligned} \quad (22)$$

Table 1. Parameters of HGSO algorithm for PSS design

HGSO Parameter	Value
Gas particle (swarm size)	50
Maximum iteration number	30
$[l_1\ l_2\ l_3]$	[0.05 100 0.01]
$[c_1\ c_2\ \beta\ \alpha\ K]$	[0.1 0.2 1 1 1]
Variable number	3 (K_{PSS}, T_1 and T_2)
Lower bound of $[K_{PSS}\ T_1\ T_2]$	[0.1 0.01 0.01]
Upper bound of $[K_{PSS}\ T_1\ T_2]$	[50 1.5 1.5]
Independent run number	20
Simulation time (T_{sim})	10 sec

HGSO: Henry gas solubility optimization; PSS: power system stabilizer

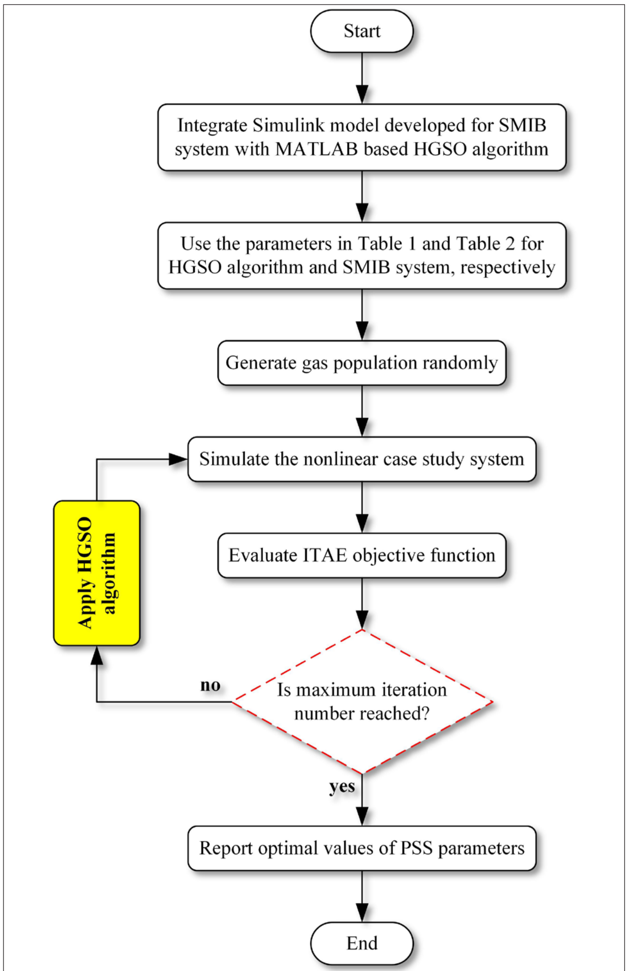

Figure 5. Detailed flowchart of the suggested HGSO-based PSS controller design.
HGSO, Henry gas solubility optimization; PSS, power system stabilizer

Table 2. Parameters of the SMIB system

Transmission line	R_e=0.0 pu, X_e=0.4 pu
Generator	χ_d=1.6 pu, χ_q=1.55 pu, χ'_d=0.32 pu, T'_{d0}=6.0 sec, H=3.0 sec, D=0
Operating point	P=0.8 pu, Q=0.4 pu, V_∞=1.0 pu, f=60.0 Hz
Exciter	K_A=50, T_A=0.05 sec
Heffron–Phillips model constants	K_1=1.1775, K_2=1.0783, K_3=0.3600, K_4=1.3803, K_5=-0.0054, K_6=0.4603

SMIB: single-machine infinite-bus

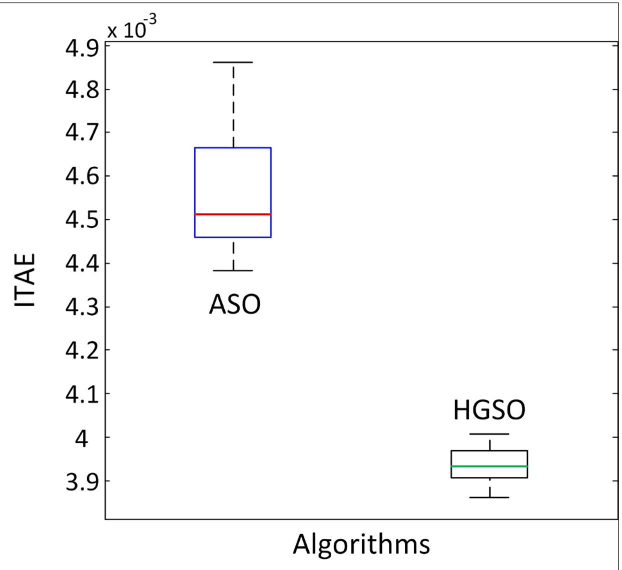

Figure 6. Comparative boxplot analysis results for ASO and HGSO algorithms.
ASO, atom search optimization; HGSO, Henry gas solubility optimization

The proposed design approach for PSS employed in a SMIB system is subjected to large fault conditions while the objective function given in (21) is considered. The HGSO algorithm was employed to solve this nonlinear optimization problem and search for an optimal set of PSS parameters (K_{PSS}, T_1 and T_2). The computational flowchart of the HGSO algorithm is represented in Figure 5.

Case Study

In this section, the superiority of the recommended HGSO algorithm for designing a PSS is shown compared with conventional PSS and an optimized PSS controller based on the ASO algorithm (see [21] for more details about the problem solution) via various analyses.

SMIB Test System

The SMIB power system data used to design of the PSS are listed in Table 2 [2]. In addition, the conventional PSS parameters,

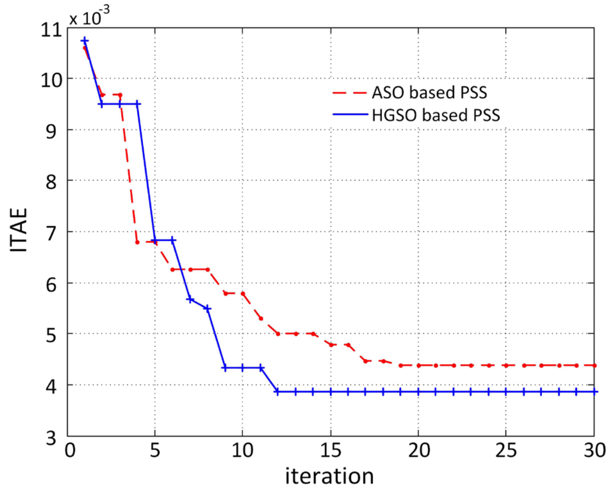

Figure 7. Convergence curves for ASO and HGSO algorithms. ASO, atom search optimization; HGSO, Henry gas solubility optimization

with values of K_{PSS}= 0.5, T_1= 0.5 sec, and T_2= 0.1 sec, were taken from [2]. The stated traditional PSS design procedure is a complicated frequency domain method and thus requires intensive calculations; see [2] and [20] for detailed information.

Statistical Analysis via Boxplots

The consistency of the solution achieved by the ASO and HGSO algorithms is very important for investigating their performance; therefore, nonlinear simulations were conducted 20 times for both. The values of the ITAE objective function from 20 simulations for the SMIB power system are given as boxplots shown in Figure 6. According to an analysis of the boxplots, the value of ITAE achieved by the HGSO algorithm has a more consistent spread in a narrower region compared with that achieved by the ASO algorithm.

Convergence Rate Analysis

The respective convergence speeds of the ITAE objective function for best runs of the HGSO and ASO are depicted in Figure 7. It is clear from the convergence plot that the HGSO algorithm reaches the lowest ITAE value with the minimal, i.e., 12, iterations. The final values of the optimized PSS parameters after the best runs of ASO and HGSO are given in Table 3.

Eigenvalue Stability Analysis

Eigenvalue analysis was used to investigate the small signal stability behavior of a power system by considering different characteristic frequencies. In a power system, the stability of eigenvalues (to be in the left side of the s–plane) is not the only criteria for stability. The desired eigenvalues must also be damped as quickly as possible for electromechanical oscillations. Considering this, eigenvalue analysis was performed to verify that the proposed HGSO-based controller improves the linear model stability of the system.

Table 3. PSS controller parameters obtained

Parameters	ASO	HGSO
K_{PSS}	45.9602	20.9794
T_1	0.4781	0.4512
T_2	0.0146	0.0100

ASO: atom search optimization; HGSO: Henry gas solubility optimization; PSS: power system stabilizer

Table 4. System eigenvalues and damping ratios

Damping Controller Type	Eigenvalue (λ=σ±jω)	Damping Ratio $(\xi = -\frac{\sigma}{\sqrt{\sigma^2+\omega^2}})$
No stabilizer (without controller)	-14.5667	1.0000
	-5.7345	1.0000
	-0.0809+8.5518*i*	0.0095
	-0.0809-8.5518*i*	0.0095
Conventional PSS [2]	-0.1739+8.6660*i*	0.0201
	-0.1739-8.6660*i*	0.0201
	-15.5041	1.0000
	-6.3466	1.0000
	-8.2644	1.0000
ASO-based PSS	-77.9762	1.0000
	-3.6430+25.6353*i*	0.1407
	-3.6430-25.6353*i*	0.1407
	-1.8470+2.1432*i*	0.6528
	-1.8470-2.1432*i*	0.6528
HGSO-based PSS	-103.1951	1.0000
	-5.9238+17.5419*i*	0.3199
	-5.9238-17.5419*i*	0.3199
	-2.7101+3.1504*i*	0.6521
	-2.7101-3.1504*i*	0.6521

ASO: atom search optimization; HGSO: Henry gas solubility optimization; PSS: power system stabilizer

The eigenvalues and electromechanical swing modes of the SMIB system were computed in MATLAB using the system matrix presented in (20). The system matrices without PSS and with conventional PSS [2], ASO-based PSS, and HGSO-based PSS are given in (23)–(26), respectively.

$$A_{no-stabilizer} = \begin{bmatrix} -0.4630 & -0.2300 & 0 & 0.1667 \\ 0 & 0 & 376.9911 & 0 \\ -0.1797 & -0.1962 & 0 & 0 \\ -460.2844 & 5.3753 & 0 & -20 \end{bmatrix} \quad (23)$$

$$A_{conventional-PSS} = \begin{bmatrix} -0.4630 & -0.2300 & 0 & 0.1667 & 0 \\ 0 & 0 & 376.9911 & 0 & 0 \\ -0.1797 & -0.1962 & 0 & 0 & 0 \\ -460.2844 & 5.3753 & 0 & -20 & 1000 \\ -0.4493 & -0.4906 & 5 & 0 & -10 \end{bmatrix} \quad (24)$$

$$A_{ASO-PSS} = \begin{bmatrix} -0.4630 & -0.2300 & 0 & 0.1667 & 0 \\ 0 & 0 & 376.9911 & 0 & 0 \\ -0.1797 & -0.1962 & 0 & 0 & 0 \\ -460.2844 & 5.3753 & 0 & -20 & 1000 \\ -270.4916 & -295.3579 & 3147.9589 & 0 & -68.4932 \end{bmatrix} \quad (25)$$

$$A_{HGSO-PSS} = \begin{bmatrix} -0.4630 & -0.2300 & 0 & 0.1667 & 0 \\ 0 & 0 & 376.9911 & 0 & 0 \\ -0.1797 & -0.1962 & 0 & 0 & 0 \\ -460.2844 & 5.3753 & 0 & -20 & 1000 \\ -170.1250 & -185.7646 & 2097.9400 & 0 & -100 \end{bmatrix} \quad (26)$$

All eigenvalues and corresponding damping ratios of the linearized SMIB system model without a stabilizer and with PSS controllers optimized by ASO and HGSO algorithms are given in Table 4. This table also includes the system eigenvalues and damping ratios for conventional PSS for comparison, and shows that the system is insufficiently damped when PSS is not utilized. Compared with conventional PSS and ASO-based PSS designs, the eigenvalues of the proposed HGSO-based PSS are farther to the left of the s–plane and there has a better minimum damping ratio. Therefore, an HGSO-based PSS greatly enhances the small signal stability of the SMIB system and improves the damping characteristics of electromechanical modes.

Stability Analysis in Nonlinear Model

Mathematical models of the differential and algebraic equations of the SMIB power system were created using various Simulink blocks. The developed Simulink model was used for nonlinear simulations. In a MATLAB/Simulink environment, time domain simulations were performed using the ode4 (Runge–Kutta) method with an integration step of Δt=0.005 sec for numerical integration of differential equations. This section provided the stability analysis, which was carried out using the nonlinear model, to clearly demonstrate the quality of the proposed HGSO-based PSS controller.

A three-phase fault was applied at the generator terminal busbar at t=2s and cleared after three cycles (0.05 s). The original system was restored on fault clearance. The system rotor angle (δ), speed deviation (Δω), and electrical power (P_e) responses are shown in Figures 8, 9, and 10, respectively. It is obvious from these figures that the power system oscillations are inadequately damped, although the system is stable, without any controller and with conventional PSS. The stability of the SMIB system was maintained and the oscillations of the power system were effectively suppressed with the application of an ASO-based PSS. In addition, unlike conventional and ASO-based PSSs, the oscillations in the δ, Δω, and P_e were prevented with the employment of the proposed HGSO-based PSS controller. Moreover, it provided good damping characteristics to low-frequency oscillations by quickly stabilizing the system.

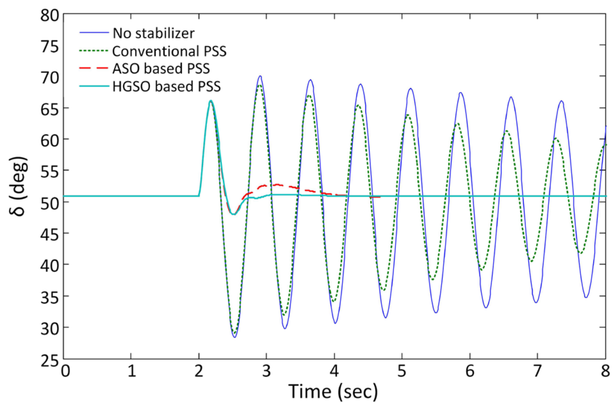

Figure 8. Change in rotor angle (δ)

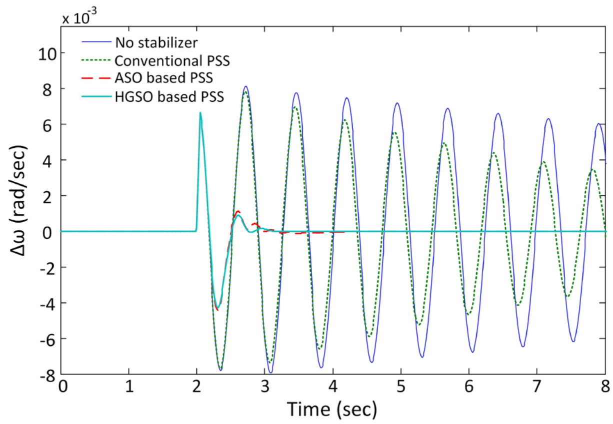

Figure 9. Change in speed deviation (Δω)

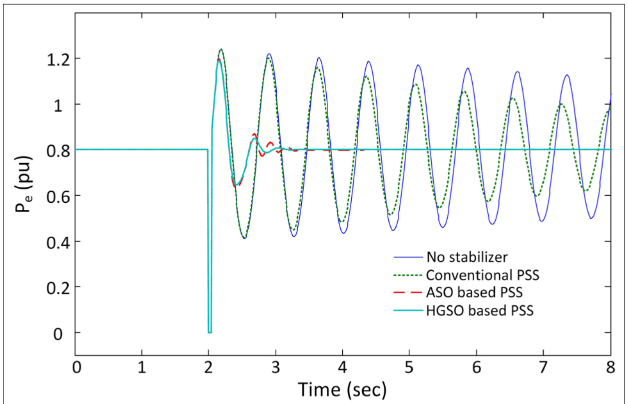

Figure 10. Change in electrical power (P_e)

Conclusion

A novel metaheuristic optimization method, inspired by the behavior of gas governed by Henry's law, has been suggested for optimal tuning of PSS parameters K_{PSS}, T_1, and T_2. For the design problem, an ITAE objective function was minimized using an HGSO algorithm to improve the dynamic performance of the power system. The performance of the proposed PSS controller was tested on a SMIB system and compared with ASO-based and conventional PSS controllers. Analysis of the eigenvalues obtained and results of nonlinear simulations demonstrated that the HGSO-tuned PSS controller was capable of significant suppression of electromechanical oscillations. In addition, the HGSO algorithm was shown to provide good statistical performance and high convergence speed for a PSS design employed in a SMIB system.

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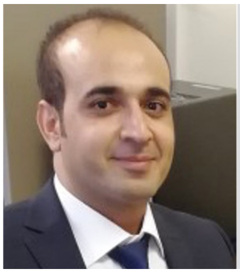

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