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Enhancing Grid Stability through an Adaptive Genetic Optimization Framework for Power System Stabilizer Control

Anusiyaayodhi A
Department of Electrical and Electronics Engineering, Vikrant University, Gwalior, Madhyapradesh, India.

Dr. Brijendra Mishra
Department of Electrical and Electronics Engineering, Vikrant University, Gwalior, Madhyapradesh, India.

Abstract

Power system stabilizers (PSS) play a crucial role in damping low-frequency oscil-lations and maintaining dynamic stability in modern electrical grids. However, conventional PSS tuning methods often struggle to adapt to varying operating conditions and the increasing complexity introduced by renewable energy inte-gration. This paper presents an adaptive genetic optimization framework for PSS parameter tuning that enhances grid stability across diverse operating scenarios. The proposed approach employs a multi-objective genetic algorithm (GA) that simultaneously optimizes damping ratio, settling time, and overshoot char-acteristics while accounting for system nonlinearities and uncertainties. An adaptive mechanism continuously monitors grid conditions and triggers real-time parameter adjustment when significant deviations are detected, ensuring robust performance under changing load profiles and network configurations.

The framework incorporates a comprehensive fitness function that evaluates system responses to various disturbances, including three-phase faults, load variations, and generator outages. To assess the effectiveness of the proposed technique, a comprehensive evaluation is performed using MATLAB/Simulink-based simulations. Simulation studies conducted on test system demonstrate that the proposed adaptive GA-based PSS controller achieves superior damping performance compared to conventional PSS and fixed-parameter GA-tuned con-trollers, reducing settling times by up to 40% and improving damping ratios by 25-35% s.

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The results validate the framework's effectiveness in maintaining stability under
dynamic conditions, offering a promising solution for modern power systems facing unprecedented operational challenges.

Keywords: Power System Stabilizer (PSS), Adaptive Control, Genetic Algorithm (GA), Multi-Objective Optimization, Small-Signal Stability, Eigenvalue Analysis, Damping Enhancement, Synchronous Generator

1 Introduction

1.1 Background and Motivation

Power systems are increasingly exposed to low-frequency oscillations arising from high loading, weak grid conditions, and the widespread penetration of renewable energy sources (RESs). These oscillations pose a significant threat to system stability, often degrading damping characteristics and risking inter-area instability. Power System Stabilizers (PSS) have traditionally been deployed to enhance the damping of electromechanical oscillations by modulating generator excitation. However, the effectiveness of conventional PSS tuning diminishes under varying operating conditions, nonlinear system dynamics, and uncertainties introduced by renewable energy integration and changing network configurations [1, 2].

Most utilities still rely on classical tuning methods such as phase compensation or fixed-parameter optimization, which are designed around a limited number of operating points. As a consequence, these tuned PSS settings may become suboptimal or even destabilizing when subjected to disturbances, topology changes, or shifting generation patterns [3]. The need for adaptive and robust tuning methodologies is therefore more critical than ever. Recent studies have explored intelligent and evolutionary optimization techniques to improve PSS performance in complex, nonlinear, and time-varying environments [4, 5]. Among these, Genetic Algorithms (GAs) have emerged as a promising approach due to their global search ability, robustness against non-convexity, and suitability for multi-objective optimization.

Nevertheless, existing GA-based approaches typically rely on offline tuning and do not adapt in real time to system variations. Their lack of responsiveness to dynamic changes in grid conditions restricts their effectiveness in modern power networks characterized by rapid fluctuations and wide operational uncertainty [6]. This motivates the development of an adaptive optimization mechanism that continuously evaluates system performance and updates controller parameters to ensure consistent damping behavior across operating scenarios.

1.2 Literature Review

A wide range of methodologies have been explored to improve PSS performance, including fuzzy logic controllers [7], model predictive controllers [8], hybrid neuro-fuzzy techniques [9], and heuristic optimization-based tuning [10]. While these methods

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demonstrate improved performance over classical designs, many suffer from computational complexity, slow convergence, or lack of real-time adaptability. Evolutionary algorithms such as Particle Swarm Optimization (PSO), Differential Evolution (DE), Ant Colony Optimization (ACO), and Genetic Algorithms (GA) have shown substantial success in optimizing PSS parameters under nonlinear and uncertain environments [11, 12].

Recent advancements propose multi-objective optimization frameworks that consider time-domain indices, frequency-domain damping ratios, and robustness against load variations [13]. However, these methods generally remain offline, limiting their ability to respond to disturbances or continuously changing grid behavior. Few studies attempt adaptive or online evolutionary tuning, and those that do often face challenges with computational burden, convergence reliability, or stability guarantees [14].

Given these limitations, a structured adaptive GA-based tuning framework that integrates real-time monitoring, multi-objective fitness evaluation, and robust search operators is essential for modernizing PSS control. Such a framework would bridge the gap between offline optimization and online adaptability while retaining algorithmic simplicity and computational efficiency.

1.3 Key Contributions

This work proposes an Adaptive Genetic Optimization Framework for enhancing the damping performance of Power System Stabilizers in multi-area power networks. The main contributions are summarized as follows:

1. A novel adaptive genetic optimization architecture is developed for real-time PSS tuning. The proposed method enables continuous parameter adjustment based on operating-point deviations, ensuring improved damping under dynamic grid conditions.
2. A multi-objective GA formulation is introduced for simultaneously optimizing damping ratio, overshoot, settling time, and robustness to uncertainties. The fitness function integrates both time-domain and frequency-domain performance metrics, making the optimization comprehensive and resilient.
3. A disturbance-sensitive adaptation mechanism is incorporated that triggers GA re-optimization during significant deviations such as load changes, generator outages, or inter-area oscillatory events.
4. Extensive simulations on a two-area benchmark power system validate the effectiveness of the proposed approach. Comparative studies show that the adaptive GA-PSS significantly enhances oscillation damping and reduces settling times compared to conventional fixed-parameter PSS and offline GA-tuned controllers.

The remainder of this paper is organized as follows: Section II presents the mathematical model of the two-area test system and PSS structure. Section III introduces the proposed adaptive genetic optimization framework. Section IV discusses stability and performance analysis. Section V provides simulation results, followed by concluding remarks in Section VI.

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2 System Modeling and Problem Formulation

2.1 Power System Dynamic Model

The synchronous generator is modeled using the classical nonlinear electromechanical swing dynamics. The rotor angle (δ) and rotor speed (ω) relative to the synchronous reference (ω_s) evolve according to the well-known swing equations:

$$\frac{d\delta}{dt} = \omega - \omega_s \tag{1}$$

$$\frac{d\omega}{dt} = \frac{1}{2H}\left(T_m - T_e - D(\omega - \omega_s)\right) \tag{2}$$

where (δ): generator electrical rotor angle (rad), (ω): mechanical rotor speed (rad/s), (ω_s): synchronous reference speed (rad/s), (H): inertia constant (s), (T_m): mechanical input torque (p.u.), (T_e): electromagnetic torque (p.u.), (D): mechanical damping coefficient (p.u.).

The electromagnetic torque is expressed using the standard Park-transformed flux–current interaction:

$$T_e = \psi_d i_q - \psi_q i_d \tag{3}$$

where (ψ_d, ψ_q): (dq)-axis stator flux linkages (p.u.), (i_d, i_q): (dq)-axis stator currents (p.u.).

The generator electrical dynamics follow the two-axis representation:

$$\frac{d\psi_d}{dt} = -R_a i_d + \omega_s \psi_q + v_d \tag{4}$$

$$\frac{d\psi_q}{dt} = -R_a i_q - \omega_s \psi_d + v_q \tag{5}$$

$$\frac{d\psi_{fd}}{dt} = -R_{fd} i_{fd} + v_{fd} \tag{6}$$

where (R_a): stator resistance (p.u.), (v_d, v_q): stator terminal voltages in (dq) frame (p.u.), (R_{fd}): field winding resistance (p.u.), (ψ_{fd}): field flux linkage (p.u.), (i_{fd}): field current (p.u.), (v_{fd}): field voltage applied through the excitation system (p.u.).

These differential relationships collectively govern the synchronous generator's electromechanical and electromagnetic interactions.

2.1.1 Excitation System Model

The IEEE Type-1 Automatic Voltage Regulator (AVR) and exciter system is modeled using a controlled amplifier–exciter–feedback loop. The amplifier output (V_R) follows:

$$\frac{dV_R}{dt} = \frac{1}{T_A}\left(-V_R + K_A(V_{ref} - V_t - V_{PSS} + V_F)\right) \tag{7}$$

where (V_R): regulator output (p.u.), (T_A): amplifier time constant (s), (K_A): amplifier gain, (V_{ref}): reference voltage (p.u.), (V_t): generator terminal voltage magnitude

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(p.u.), (V_{PSS}): supplementary PSS stabilizing signal (p.u.), (V_F): stabilizing feedback signal from exciter feedback loop (p.u.).

The exciter field voltage dynamics are:

$$\frac{dE_{fd}}{dt} = \frac{1}{T_E}\left(-K_E E_{fd} + V_R\right) \tag{8}$$

where (E_{fd}): exciter field voltage (p.u.), (K_E): exciter gain, (T_E): exciter time constant (s).

The exciter stabilizing feedback loop is modeled by:

$$\frac{dR_F}{dt} = \frac{1}{T_F}\left(-R_F + \frac{K_F}{T_F}E_{fd}\right) \tag{9}$$

where (R_F): feedback compensator state (p.u.), (K_F, T_F): stabilizer gain and time constant.

2.1.2 2.1.3 Network Model and Load Representation

The power network is represented using the nodal admittance formulation:

$$I_i = \sum_{j=1}^{n} Y_{ij} V_j \tag{10}$$

where (I_i): injected current at bus i, (Y_{ij}): element of the network admittance matrix, (V_j): complex voltage at bus j.

Real and reactive power flow at bus i are expressed as:

$$P_i = \sum_{j=1}^{n} |V_i||V_j||Y_{ij}| \cos(\theta_{ij} - \delta_i + \delta_j) \tag{11}$$

$$Q_i = -\sum_{j=1}^{n} |V_i||V_j||Y_{ij}| \sin(\theta_{ij} - \delta_i + \delta_j) \tag{12}$$

2.2 Power System Stabilizer Structure

2.2.1 Lead–Lag PSS Configuration

The PSS provides supplementary damping through a washout filter and cascaded lead–lag compensators:

$$G_{PSS}(s) = K_{PSS} \cdot \frac{sT_w}{1 + sT_w} \cdot \frac{(1 + sT_1)(1 + sT_3)}{(1 + sT_2)(1 + sT_4)} \tag{15}$$

The washout function is:

$$H_w(s) = \frac{sT_w}{1 + sT_w} \tag{16}$$

The phase compensator network contributes:

$$H_{comp}(s) = \frac{1 + sT_1}{1 + sT_2} \cdot \frac{1 + sT_3}{1 + sT_4} \tag{17}$$

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2.2.2 2.2.2 Signal Processing and Output Limits

To prevent AVR saturation and instability, the PSS output is limited as:

$$V_{PSS,min} \leq V_{PSS} \leq V_{PSS,max} \tag{18}$$

2.3 Linearized System Model for Stability Analysis

2.3.1 State-Space Representation

The nonlinear model is linearized around an equilibrium operating point to obtain:

$$\Delta\dot{x} = A\Delta x + B\Delta u \tag{19}$$

$$\Delta y = C\Delta x + D\Delta u \tag{20}$$

with state vector:

$$\Delta x = [\Delta\delta, \Delta\omega, \Delta\psi_d, \Delta\psi_q, \Delta E_{fd}, \Delta V_R, \Delta R_F, \Delta x_{PSS}]^T \tag{21}$$

Each state corresponds to the small-signal deviation of a physical quantity.

2.3.2 Eigenvalue Characterization

The system eigenvalues are computed from:

$$\det(\lambda I - A) = 0 \tag{22}$$

The oscillatory modes take the form:

$$\lambda = -\zeta\omega_n \pm j\omega_n\sqrt{1-\zeta^2} \tag{23}$$

with oscillation frequency:

$$f = \frac{\omega_n\sqrt{1-\zeta^2}}{2\pi} \tag{24}$$

A minimum stability requirement enforces:

$$\zeta \geq 0.05 \tag{25}$$

2.4 Problem Formulation

2.4.1 Control Objective

The PSS parameter set is defined as:

$$\theta_{PSS} = [K_{PSS}, T_1, T_2, T_3, T_4] \tag{26}$$

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2.4.2 2.4.2 Multi-Objective Optimization

$$\min_{\theta_{PSS}} J(\theta_{PSS}) = w_1 J_\zeta + w_2 J_{t_s} + w_3 J_{OS} + w_4 J_\lambda \tag{27}$$

with bounds:

$$K_{PSS,min} \leq K_{PSS} \leq K_{PSS,max} \tag{28}$$

$$T_{i,min} \leq T_i \leq T_{i,max}, \quad i = 1, \ldots, 4 \tag{29}$$

Minimum damping constraint:

$$\zeta_i \geq \zeta_{min} \tag{30}$$

System stability:

$$\mathrm{Re}(\lambda_i) < 0 \tag{31}$$

3 Proposed Adaptive Genetic Optimization Framework

This section presents the complete design methodology of the proposed adaptive PSS tuning framework, which integrates offline multi-objective genetic optimization with an online condition-monitoring mechanism for parameter adaptation. The formulation explicitly links PSS parameterization with the closed-loop linearized model, enabling systematic eigenvalue shaping and time-domain enhancement under varying operating conditions.

3.1 PSS Parameterization

The optimization vector collects all stabilizer coefficients as

$$\theta = [K_{\mathrm{PSS}},\, T_1,\, T_2,\, T_3,\, T_4] \tag{32a}$$

$$\theta = [K_{\mathrm{PSS}}, T_1, T_2, T_3, T_4] \tag{32b}$$

which fully characterizes the washout–lead–lag PSS structure.

For a given candidate θ, the linearized synchronous generator–AVR–PSS model introduced in Section II is augmented to incorporate the stabilizer dynamics. The resulting closed-loop matrix is expressed as

$$A_{\mathrm{cl}} = A + B\, K_{\mathrm{PSS}}\, C_{\mathrm{PSS}} \tag{33a}$$

$$A_{cl} = A + BK_{\mathrm{PSS}}C_{\mathrm{PSS}} \tag{33b}$$

This formulation explicitly reflects the influence of K_{PSS} and the compensator time constants on the small-signal behavior, ensuring that each candidate solution can be directly evaluated through modal analysis.

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3.2 Multi-Objective Fitness Formulation

The tuning objective seeks to enhance damping, transient speed, oscillation suppression, and robustness margins simultaneously. To capture all relevant performance indices, a unified multi-objective structure is adopted.

3.2.1 Damping Ratio Objective

The eigenvalues of the closed-loop system are written as

$$\lambda_i = \sigma_i \pm j\omega_i \tag{34a}$$

$$\lambda_i = \sigma_i \pm j\omega_i \tag{34b}$$

The modal damping ratio is computed as

$$\zeta_i = -\frac{\sigma_i}{\sqrt{\sigma_i^2 + \omega_i^2}} \tag{35a}$$

$$\zeta_i = -\frac{\sigma_i}{\sqrt{\sigma_i^2 + \omega_i^2}} \tag{35b}$$

Modes with inadequate damping degrade electromechanical stability; therefore, a penalty function is introduced:

$$J_\zeta = \sum_i \left(\max(0, \zeta_{\min} - \zeta_i)\right)^2 \tag{36a}$$

$$J_\zeta = \sum_i \left(\max(0, \zeta_{\min} - \zeta_i)\right)^2 \tag{36b}$$

3.2.2 3.2.2 Settling Time and Overshoot Objectives

$$J_{t_s} = \sum_{j=1}^{m} t_{s,j} \tag{37a}$$

$$J_{t_s} = \sum_{j=1}^{m} t_{s,j} \tag{37b}$$

$$J_{OS} = \sum_{j=1}^{m} \left(\frac{\Delta\omega_{\text{peak},j}}{\Delta\omega_{\text{ss},j}}\right)^2 \tag{38a}$$

$$J_{OS} = \sum_{j=1}^{m} \left(\frac{\Delta\omega_{\text{peak},j}}{\Delta\omega_{\text{ss},j}}\right)^2 \tag{38b}$$

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3.2.3 Eigenvalue Stability Margin

$$\mathrm{Re}(\lambda_i) < -\sigma_{\mathrm{margin}} \tag{39a}$$

$$\mathrm{Re}(\lambda_i) < -\sigma_{\mathrm{margin}} \tag{39b}$$

$$J_\lambda = \sum_i \left(\max(0, \, \sigma_{\mathrm{margin}} + \mathrm{Re}(\lambda_i))\right)^2 \tag{40a}$$

$$J_\lambda = \sum_i \left(\max(0, \, \sigma_{\mathrm{margin}} + \mathrm{Re}(\lambda_i))\right)^2 \tag{40b}$$

3.2.4 Combined Fitness Function

$$F(\theta) = w_1 J_\zeta + w_2 J_{t_s} + w_3 J_{OS} + w_4 J_\lambda \tag{41a}$$

$$F(\theta) = w_1 J_\zeta + w_2 J_{t_s} + w_3 J_{OS} + w_4 J_\lambda \tag{41b}$$

3.3 3.3 Genetic Algorithm Operations

Selection probability:

$$P_i = \frac{1/F_i}{\sum_k 1/F_k} \tag{42a}$$

$$P_i = \frac{1/F_i}{\sum_k 1/F_k} \tag{42b}$$

Arithmetic crossover:

$$\theta_d = \alpha\theta_1 + (1-\alpha)\theta_2 \tag{43a}$$

$$\theta_d = \alpha\theta_1 + (1-\alpha)\theta_2 \tag{43b}$$

Mutation:

$$\theta_{\mathrm{mut}} = \theta + \mu(\theta_{\max} - \theta_{\min}) \tag{44a}$$

$$\theta_{\mathrm{mut}} = \theta + \mu(\theta_{\max} - \theta_{\min}) \tag{44b}$$

3.4 Adaptive Monitoring Mechanism

$$\mathrm{OCI}(t) = \left[\frac{P_L(t)}{P_{L0}}, \; \frac{Q_L(t)}{Q_{L0}}, \; V(t)\right] \tag{45a}$$

$$\mathrm{OCI}(t) = \left[\frac{P_L(t)}{P_{L0}}, \; \frac{Q_L(t)}{Q_{L0}}, \; V(t)\right] \tag{45b}$$

Deviation index:

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$$\Delta \mathrm{OC} = \sum_i \left(\mathrm{OCI}_i(t) - \mathrm{OCI}_{i0}\right)^2 \quad (46a)$$

$$\Delta \mathrm{OC} = \sum_i \left(\mathrm{OCI}_i(t) - \mathrm{OCI}_{i0}\right)^2 \quad (46b)$$

Trigger conditions:

$$\Delta \mathrm{OC} > \Delta_{\mathrm{thr}} \quad (47a)$$

$$\Delta \mathrm{OC} > \Delta_{\mathrm{thr}} \quad (47b)$$

$$\min_i(\zeta_i) < \zeta_{\mathrm{crit}} \quad (48a)$$

$$\min_i(\zeta_i) < \zeta_{\mathrm{crit}} \quad (48b)$$

3.5 Parameter Update and Deployment

$$\theta(k+1) = \alpha\theta_{\mathrm{new}} + (1-\alpha)\theta(k) \quad (49a)$$

$$\theta(k+1) = \alpha\theta_{\mathrm{new}} + (1-\alpha)\theta(k) \quad (49b)$$

4 Results and Analysis

4.1 System Under Study

The system considered in this study is a single-machine infinite-bus (SMIB) configuration equipped with a conventional IEEE-type exciter and a power system stabilizer (PSS), as illustrated in Figure 1. The generator is modeled using the classical 4th-order synchronous machine model, incorporating both electromechanical swing dynamics and field winding dynamics to capture low-frequency oscillatory behavior.

The stabilizer input is derived from speed deviation, which is processed through a washout stage and a dual-stage lead–lag compensator. The proposed adaptive Genetic Algorithm (GA)-based PSS continuously monitors system operating conditions and adjusts key stabilizer parameters—gain, phase-compensation time constants, and washout parameters—to maximize damping performance.

The infinite bus is represented using a Thevenin equivalent, while the transmission system is modeled using standard π-line parameters to ensure accurate representation of electrical interactions. Disturbances such as three-phase faults, load perturbations, and parametric variations are applied to test the robustness of the stabilizer. This SMIB configuration remains the most widely accepted benchmark for oscillation damping performance evaluation, providing clear visibility into generator dynamics and control interactions.

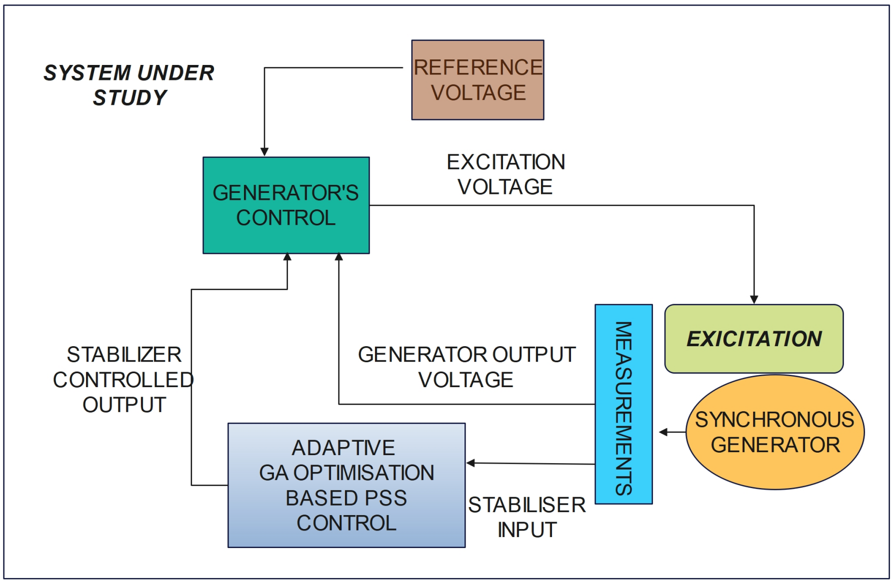

Fig. 1 System Under Study

4.2 Output Power Response

Figure 2 illustrates the generator electromagnetic output power response following a disturbance. Without adaptive tuning, the system exhibits low-frequency oscillations characterized by slow damping and elevated oscillatory magnitude. With the proposed adaptive GA-based PSS, the oscillations decay significantly faster, demonstrating the stabilizer's ability to inject supplementary damping torque in phase with the speed deviation. The GA-optimized lead–lag structure provides accurate phase compensation across the oscillatory frequency range, thereby increasing the effective damping ratio of the dominant electromechanical mode. Consequently, the system reaches steady-state output power more rapidly, with minimized overshoot and reduced transient energy exchange between mechanical and electrical subsystems.

4.3 Rotor Speed Dynamics

Figure 3 shows the rotor speed dynamics, which represent the generator's inertial response. Under conventional PSS tuning, the rotor speed displays oscillatory swings driven by the mismatch between mechanical input and electrical output during disturbance recovery. The adaptive GA-based PSS significantly enhances rotor speed stabilization by dynamically updating stabilizer parameters according to prevailing system conditions. This prevents parameter drift under varying load levels and transmission network changes. The improved damping performance ensures that

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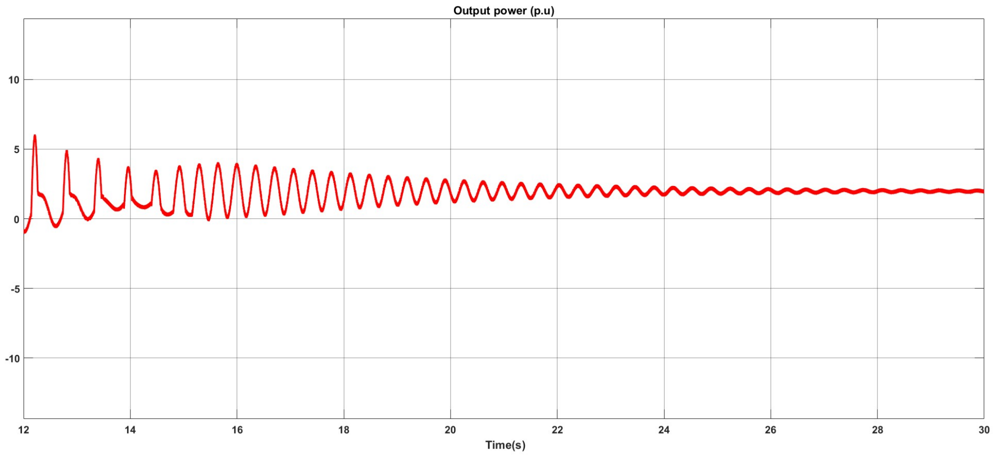

Fig. 2 Output power response of the system

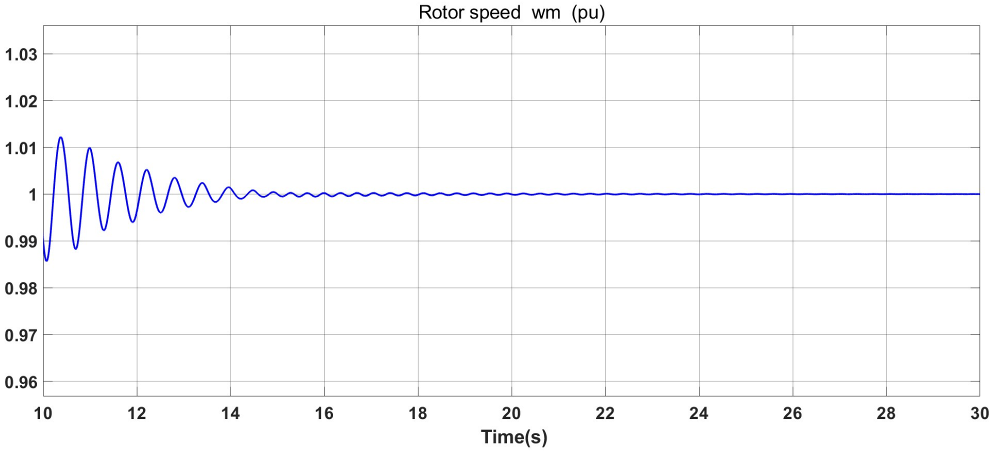

Fig. 3 Rotor Speed

rotor speed quickly converges to synchronous value, suppressing prolonged oscillatory motion and preventing rotor-angle divergence. This confirms t hat t he proposed method strengthens the system's synchronous stability margin.

4.4 Speed Deviation Performance

The speed deviation ($\Delta\omega$) response presented in Figure 4 further validates the controller's ability to suppress low-frequency electromechanical oscillations. Under the proposed stabilizer, $\Delta\omega$ oscillations exhibit a steep decay profile, reflecting significantly enhanced modal damping. The adaptive mechanism ensures that the PSS gain and compensator time constants remain optimal even when system nonlinearities, loading

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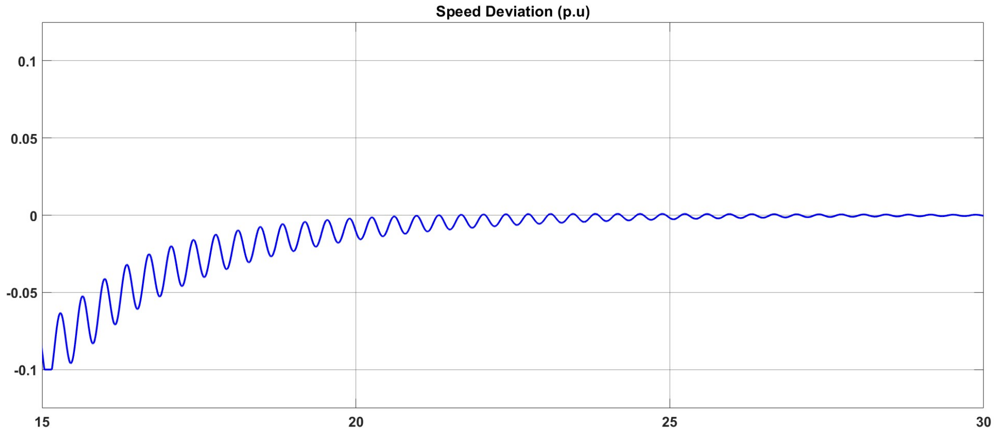

Fig. 4 speed deviation Response to a time change

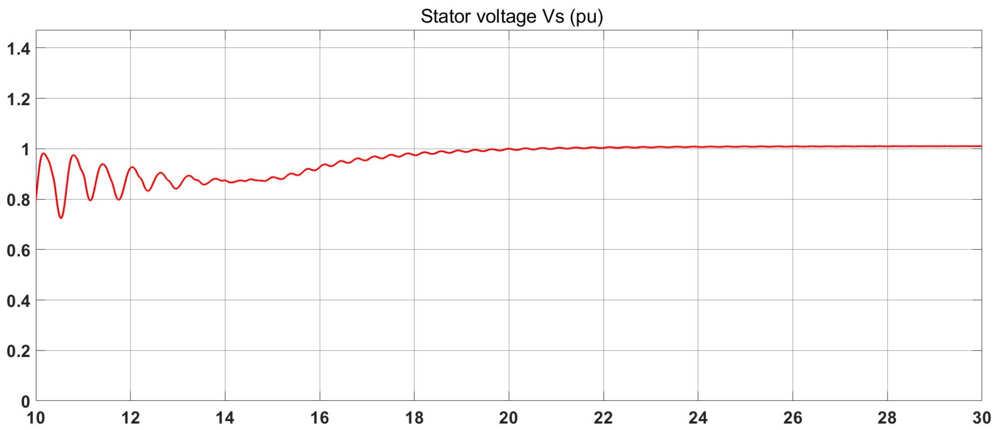

Fig. 5 Stator voltage

conditions, or operating points shift. This real-time optimization capability is particularly beneficial under stressed grid conditions, where conventional fixed-parameter PSS typically loses effectiveness. As a result, the speed deviation settles within a shorter time interval, demonstrating improved transient stability performance and enhanced resilience against fault-induced disturbances.

4.5 Stator Terminal Voltage Response

Figure 5 presents the stator terminal voltage (V_t) behavior following a disturbance. Voltage oscillations represent the interaction between the excitation system and the generator's internal reactances. Traditional PSS designs often provide limited damping

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to voltage-related oscillations due to fixed parameterization. The proposed GA-based stabilizer improves voltage regulation by enhancing damping of both electrical and electromechanical modes. The voltage reaches steady-state more rapidly, with reduced oscillatory amplitude, demonstrating effective coordination between the PSS and the automatic voltage regulator (AVR). This improvement contributes to superior dynamic voltage stability, preventing undesirable interactions such as exciter-induced oscillations or control-loop interference common in high-gain excitation systems.

Conclusion

This paper presented an adaptive genetic algorithm-based framework for power system stabilizer (PSS) parameter tuning, aimed at enhancing damping of low-frequency oscillations and maintaining dynamic stability in modern power grids. The proposed approach effectively combines multi-objective optimization with real-time adaptability, enabling the PSS to respond to varying operating conditions, network uncertainties, and disturbances such as faults and load variations. Simulation results on the test system demonstrated that the adaptive GA-based PSS significantly outperforms conventional and fixed-parameter GA-tuned controllers, achieving faster settling times, higher damping ratios, and improved overall system stability. These findings validate the effectiveness and robustness of the proposed method, highlighting its potential as a practical solution for modern power systems integrating renewable energy sources and facing increasingly complex operational challenges.

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Declarations

Declaration of interests

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The authors confirm that the data supporting the findings of this study are available within the article and raw data that support the findings of this study are available from the corresponding author upon reasonable request.