Enhanced Damping of Power Oscillations Using a Advance Optimized-Tuned Deep Neural Framework for Power System Stabilizer Design

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Abstract— **Large-scale interconnections and a variety of structural configurations have made modern power networks more complex, making them more vulnerable to disruptions like low-frequency electromechanical oscillations, transmission faults, and generator outages. Effective damping techniques are essential because low-frequency oscillations are one of the main threats to safe and dependable system operation. In this work, a Convolutional Neural Network (CNN) with hyperparameters optimized using the Grey Wolf Optimizer (GWO) is integrated into an advanced Power System Stabilizer (PSS) design. To guarantee adaptive and reliable stabilizer performance, GWO is used to systematically tune the CNN structure, including convolutional layers and filter dimensions. Extensive simulations under a range of operating conditions are used to test the proposed GWO-CNN-based PSS on a Single-Machine Infinite Bus (SMIB) system. The suggested method's improved damping capability is highlighted by a comparison with traditional PSS designs, proving its efficacy in reducing oscillations and enhancing system stability in general.**

Index Terms— **Power system stabilizer, Power oscillation, Deep neural network, Convolutional neural network, Grey wolf optimization, power oscillation, single machine infinite bus test system.**

I. Introduction

Variable generation levels, fluctuating load demands, and frequent disturbances like faults, transmission line outages, and generator tripping events have made modern power systems more and more characterized by nonlinear dynamics and operational uncertainty [1,2]. These issues pose ongoing challenges for utilities globally and have a substantial impact on the security and dependability of electric grids [3,4]. Low-frequency electromechanical oscillations are one of the most important stability issues; in the absence of sufficient damping, they could develop into widespread instability or even large-scale blackouts [5,6,7]. To reduce these oscillations and enhance system dynamic performance, conventional power system stabilizers (PSSs) have been in use for a long time [8,9]. The creation of flexible and effective PSS structures is still a top research priority because of their significance [10,11]. In general, PSS tuning techniques fall into two categories: optimization-based methods and control theory-based methods [12]. While optimization strategies offer flexibility and adaptability, they frequently face computational intensity that prevents real-time application, while control-oriented approaches offer analytical rigor but rely on extensive computations and detailed system modeling [13,14].

The ability of Artificial Intelligence (AI) techniques to learn from data and manage nonlinear, time-varying operating conditions has garnered significant attention in power system research in recent years [15,16]. AI-based frameworks for PSS design are still largely unexplored, despite their successful application in other fields [17,18]. Although earlier research has demonstrated that Artificial Neural Networks (ANNs) can improve damping performance, more sophisticated models like Convolutional Neural Networks (CNNs) have not yet been thoroughly studied in this regard. Inspired by this gap, the current work suggests a novel PSS design that combines the Grey Wolf Optimizer (GWO) and CNN learning capability to achieve improved damping. To ensure effective training and robust generalization, the GWO algorithm is used to optimize important CNN hyperparameters, such as the number of convolutional layers and filter structures [19,20]. The optimized CNN is trained to estimate PSS parameters that enhance the system's oscillation suppression capabilities using real power, reactive power, and terminal voltage as input features. A linearized transfer function model is used to implement the suggested GWO-CNN-based stabilizer on a Single-Machine Infinite Bus (SMIB) test system, and it is assessed under a range of transient operating conditions [20].

Using GWO to fine-tune CNN hyperparameters for PSS design, incorporating phase compensation to derive stabilizer parameters, mapping input operating variables to PSS parameter outputs using GWO-optimized CNN, extensively validating the proposed design across a wide range of disturbances, and comparing it to conventional PSSs reveals a clear improvement in damping performance and overall system stability.These are the main contributions of this research.

II. Modeling of the Test System and Problem Formulation

A Single-Machine Infinite Bus (SMIB) configuration with a high-gain fast exciter, modeled by the IEEE Type-I excitation system and characterized by gain parameters K_1 to K_6, is the subject of the analysis in this work . Fig. 1 shows the test network's condensed single-line representation. In this configuration, a long transmission line connects the synchronous generator to an infinite bus, and the stator resistance of the generator is assumed to be zero ($R_s = 0$). An equivalent impedance ($R_e + jX_e$) represents the transmission medium, where R_e and X_e stand for external resistance and reactance, respectively . As shown in Fig. 1, the machine supplies the infinite bus with both active and reactive power when the terminal voltage V_g is present. Fig. 2 displays the corresponding transfer function model of the SMIB system, which captures the electromechanical interactions of the generator, excitation system, and stabilizer.

This study's main goal is to create a sophisticated Power System Stabilizer (PSS) that will reduce low-frequency oscillations within the SMIB framework. The Grey Wolf Optimizer (GWO) is used to systematically optimize the architecture and hyperparameters of a Convolutional Neural Network (CNN)-based PSS for this purpose. This ensures robust damping in a variety of transient scenarios. Fig. 3 shows the suggested stabilizer integrated into the system, and Fig. 4 shows the related transfer function model, emphasizing the stabilizer's contribution to bettering system dynamics as a whole.

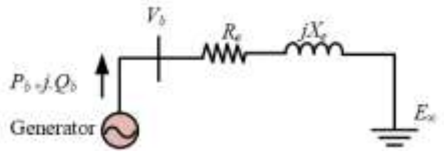

Fig. 1. Single line diagram of studied system

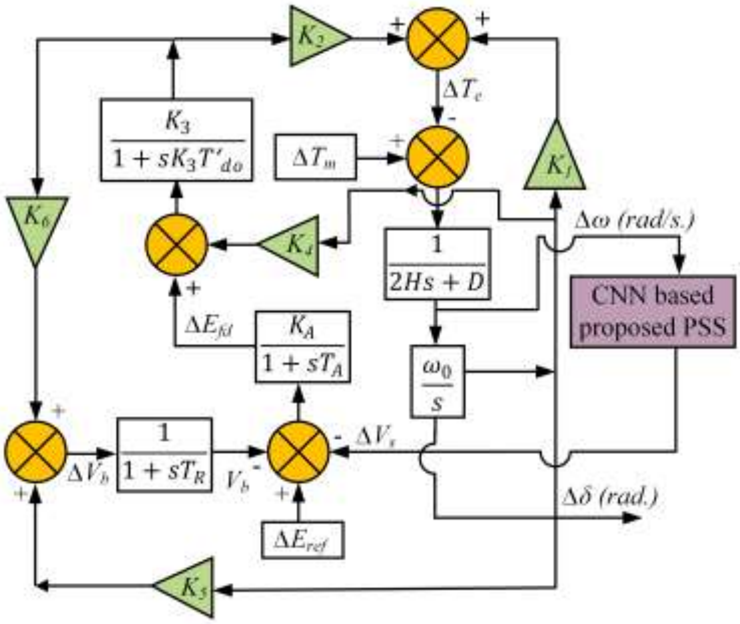

Fig. 2. Transfer function model of SMIB

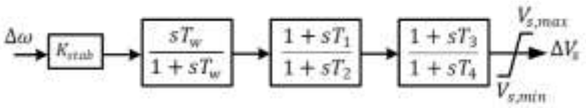

Fig. 3. Proposed power system stabilizer

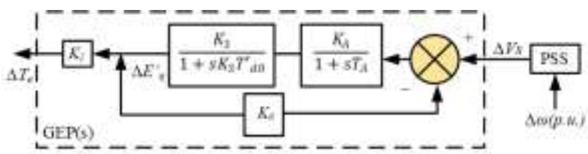

Fig. 4. GEP(s) transfer function model

III. STRUCTURE OF THE PROPOSED POWER SYSTEM STABILIZER

A traditional lead-lag compensator is used by the proposed Power System Stabilizer (PSS), which is depicted in Fig. 3. The lead element is defined by τ_ℓ, whereas the lag element is linked to a time constant τ_g. The stabilizer also includes a washout filter controlled by the time constant τ_w and an overall gain K_{pss}. System-specific coefficients C_1 through C_6 determine how these parameters should be chosen, which is directly tied to the dynamics of the generator and excitation system. A precise assessment of these coefficients guarantees that the stabilizer is set up correctly. The most effective value of K_{pss} is also determined by the exciter time constant τ_{ex} and exciter gain K_{ex}. Using rotor speed deviation $\Delta\omega_r$ as its input to generate the stabilizing voltage, the PSS enhances the damping of low-frequency oscillations by altering the inherent phase lag present in the system response.

In order to counterbalance oscillations, an electrical torque component must be created by keeping the stabilizer output ΔV_{stab} in phase with the rotor speed deviation $\Delta\omega_r$. Proper tuning is necessary to mitigate the misalignment caused by the natural phase lag between ΔV_{stab} and the corresponding electrical torque. This misalignment is further influenced by variations in gain, specifically represented by C_6. The necessary phase lead compensation is provided by choosing the time constants τ_ℓ, τ_g, τ_1, and τ_2 according to the current system conditions. The washout constant τ_w, which is usually selected between 1 and 20 seconds, needs to be big enough to guarantee sensitivity only to oscillatory components, ignoring steady-state signals. The right value of K_{pss} is also heavily influenced by the damping ratio ξ, underscoring the necessity of carefully adjusting all stabilizer parameters to ensure the best possible damping performance in the power network.

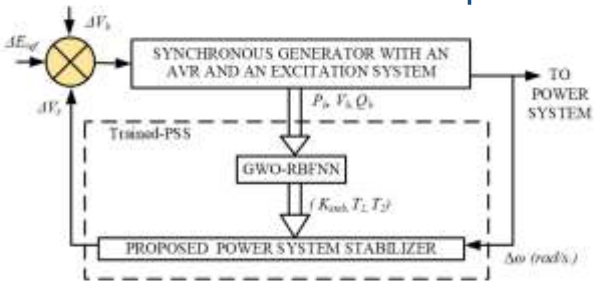

Fig. 5. PSS parameter tuning process for SMIB system

IV. Mathematical Formulation

Following the approach in, the steady-state operating conditions of the generator are obtained by first evaluating the terminal current. At the generator bus, the current can be written as

$$I_m e^{j\theta} = \frac{P_t - jQ_t}{\overline{V_t}} = \frac{P_t - jQ_t}{V_t e^{-j\delta}},$$

where P_t and Q_t represent the active and reactive power at the generator terminal, V_t is the terminal voltage magnitude, and δ denotes its phase angle. This formulation corresponds to the SMIB arrangement shown in Fig. 1, where the machine is linked to the infinite bus through an equivalent reactance X_{eq}.

The infinite bus voltage, referred to as E_{ref}, can therefore be expressed as

$$E_{ref} = V_t + jX_{eq}\left(\frac{P_t - jQ_t}{\overline{V_t^*}}\right).$$

In this study, E_{ref} is assumed to be 1 p.u. and is taken as the reference voltage. The terminal voltage can be represented in dq form as $(V_{td} - jV_{tq})$. By expanding into its real and imaginary components, the following expressions are obtained:

$$1 = V_{td} - \frac{X_{eq}\left(P_t\sqrt{V_t^2 - V_{td}^2} - Q_t V_{td}\right)}{V_t^2},$$

$$0 = \sqrt{V_t^2 - V_{td}^2} + \frac{X_{eq}\left(P_t V_{td} + Q_t\sqrt{V_t^2 - V_{td}^2}\right)}{V_t^2}.$$

From above equation, the value of Q_t can be directly determined when $E_{ref} = 1$ p.u. Hence, measurable outputs such as active power, reactive power, and terminal voltage are used as input features for the proposed GWO-tuned Convolutional Neural Network (CNN). The overall tuning process is illustrated in Fig. 5, where the CNN generates the parameters of the lead–lag compensator, namely the time constants τ_1, τ_2, τ_3, and τ_4, along with the stabilizing gain K_{cn}. To maintain a symmetrical compensator design, this study adopts the condition $\tau_1 = \tau_3$ and $\tau_2 = \tau_4$.

V. Tuning Strategy for the Proposed PSS Parameters

The tuning of the Convolutional Neural Network (CNN)-based Power System Stabilizer (PSS) is performed using a phase compensation technique. The procedure begins with calculating the lead compensator time constants at the resonant frequency $s = j\omega_{res}$, where ω_{res} represents the system resonance point. At this critical frequency, the phase angle of the combined generator–exciter–PSS (GEP) transfer function, denoted as ϕ_{sys}, is determined. The purpose of phase compensation is to ensure that the compensatory supplies sufficient phase led to counterbalance the inherent lag of the system. The time constants of the lead network, τ_a and τ_b, are derived from the following relations:

$$\omega_{res} = \sqrt{\frac{C_1\omega_s}{2J}}, \quad \lambda = \frac{1 + \sin\left(\frac{\phi_{sys}}{2}\right)}{1 - \sin\left(\frac{\phi_{sys}}{2}\right)},$$

$$\tau_a = \frac{1}{\omega_{res}\sqrt{\lambda}}, \quad \tau_b = \lambda\tau_a,$$

where ω_s denotes the synchronous speed, C_1 is a system gain constant, and J is the equivalent moment of inertia. The parameter λ establishes the ratio between lead and lag time constants based on the required phase compensation angle.

The stabilizing gain K_{cn} plays a crucial role in achieving the desired damping ratio ξ. It is calculated as

$$K_{cn} = \frac{2\xi\omega_{res}M_{sys}}{C_2\,|G_c(j\omega_{res})|\,|GEP(j\omega_{res})|},$$

where M_{sys} is the system inertia constant, C_2 is derived from system characteristics, and $G_c(j\omega_{res})$ and $GEP(j\omega_{res})$ denote the frequency responses of the compensator and GEP models respectively.

The calculated parameters τ_a, τ_b, and K_{cn} obtained from phase compensation serve as reference values for the CNN-based PSS. The CNN architecture is further fine-tuned using the Grey Wolf Optimizer (GWO), which adjusts its hyperparameters to ensure that the stabilizer enhances damping performance and adapts effectively to varying system dynamics.

VI. Proposed Methodology

Convolutional Neural Networks (CNNs) have emerged as powerful models for handling complex nonlinear relationships and identifying spatial features across a wide range of engineering domains. Unlike conventional Artificial Neural Networks (ANNs), CNNs achieve reduced computational effort through mechanisms such as local connectivity and weight sharing, which make them particularly effective in applications requiring fast and accurate learning. In this study, CNNs are employed to support the tuning of Power System Stabilizer (PSS) parameters, leveraging their strong feature extraction ability to enhance damping performance.

The structure of a CNN generally comprises convolutional layers, pooling layers, and fully connected layers. Convolutional layers apply multiple filters to extract feature representations from input data, with nonlinear activation functions used after each convolution step. Mathematically, the convolution process can be expressed as

$$F_o(i,j) = \sum_{m=1}^{M} \sum_{n=1}^{N} W\,(m,n) \cdot I(i+m-1, j+n-1) + b,$$

where $I(i,j)$ is the input feature matrix, $W(m,n)$ represents the filter weights, b is the bias, and $F_o(i,j)$ denotes the output feature map. After convolution, pooling layers are applied to downsample the resulting maps, reducing computational complexity while also limiting overfitting. Finally, fully connected layers integrate the extracted features for the estimation of PSS parameters. By combining these elements, CNN provides an adaptive framework capable of capturing system behavior and delivering optimized stabilizer settings for improved oscillation damping.

VII. Overview of Grey Wolf Optimizer (GWO)

The Grey Wolf Optimizer (GWO) is a population-based metaheuristic inspired by the leadership hierarchy and cooperative hunting strategies observed in grey wolves. The method classifies the population into four groups—alpha (α), beta (β), delta (δ), and omega (ω)—with the alpha wolf representing the most optimal solution candidate. This social structure enables the algorithm to balance exploration and exploitation during the optimization process. The hunting mechanism is modeled by updating wolf positions relative to the estimated location of the prey, which corresponds to the best solution found so far.

The position update process is mathematically described as

$$\vec{D} = \left|\vec{C} \cdot \overrightarrow{X_{best}(t)} - \overrightarrow{X(t)}\right|,$$

$$\vec{X}(t+1) = \overrightarrow{X_{best}(t)} - \vec{A} \cdot \vec{D},$$

where t is the iteration index, $\overrightarrow{X_{best}}$ denotes the prey position (best solution), $\vec{X}$ is the current wolf position, and $\vec{A}$ and $\vec{C}$ are adaptive coefficient vectors defined as

$$\vec{A} = 2 \cdot \vec{a} \cdot \vec{r_1} - \vec{a},$$

$$\vec{C} = 2 \cdot \vec{r_2}.$$

Here, $\vec{a}$ decreases linearly from 2 to 0 over the course of iterations, while $\vec{r_1}$ and $\vec{r_2}$ are uniformly distributed random vectors within [0,1]. This adaptive mechanism guides wolves toward the prey while maintaining diversity in the population, allowing the algorithm to effectively traverse the search space and converge to high-quality solutions.

VIII. GWO-based Hyperparameter Tuning of CNN and Training Process

In the proposed framework, the Grey Wolf Optimizer (GWO) is applied to fine-tune the key hyperparameters of the Convolutional Neural Network (CNN), including the number of convolutional layers, filter dimensions, and learning rate. CNN is trained using input vectors $\mathbf{X_{train}}$ that contain measurable operating variables such as terminal voltage, active power, and reactive power, while the corresponding target vectors $\mathbf{Y_{target}}$ represent the optimal Power System Stabilizer (PSS) parameters. The integration of GWO with the CNN-based PSS design is summarized in the flow diagram shown in Fig. 6. The optimization process is guided by an objective function that minimizes the mean squared error (MSE) between predicted and reference PSS parameters, ensuring improved damping performance.

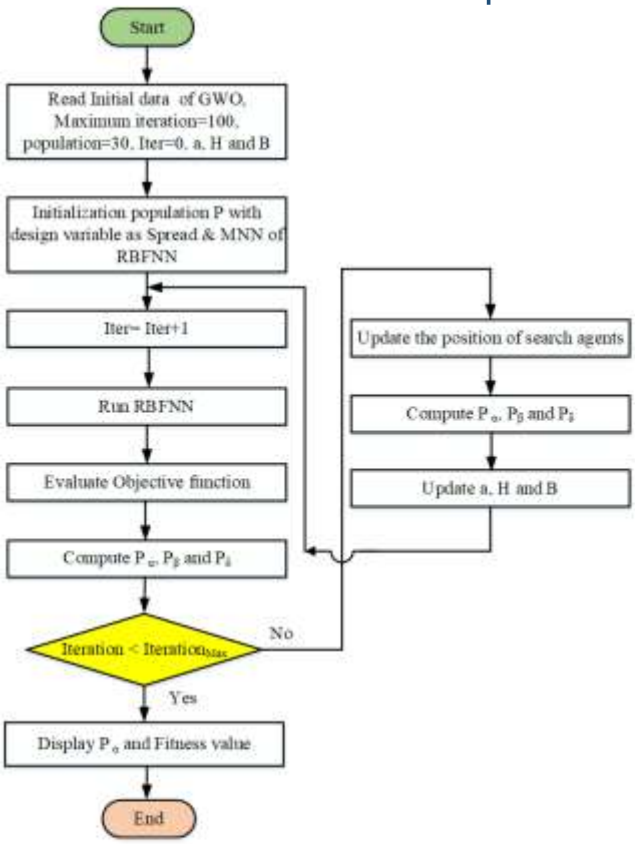

Fig. 6. Flowchart of GWO-based CNN hyperparameter tuning for PSS design

To ensure generalization across a wide range of conditions, the training dataset is generated by varying active power output (P_g), terminal voltage magnitude (V_t), and external reactance (X_{ext}) within predefined limits, while the associated reactive power (Q_g) is calculated from the system equations. The following parameter ranges are considered: P_g = 0.52–1.05 p.u., V_t = 0.88–1.12 p.u., and X_{ext} = 0.35–0.85 p.u. A total of 500 random operating points is created within these ranges, with (P_g, Q_g, V_t, X_{ext}) forming the CNN input set and the optimal stabilizer parameters serving as outputs. The GWO is configured with a population of 25 wolves and a maximum of 120 iterations. The search space for hyperparameters is defined as the learning rate between 0.001 and 0.01, the number of filters from 8 to 64, and the batch size from 16 to 128.

After training, the optimized CNN generates stabilizer parameters that closely align with analytically derived values, thereby validating its accuracy. Table I, presents results for ten representative operating scenarios, comparing parameters obtained analytically with those predicted by CNN alone and by GWO-enhanced CNN. The outcomes show that the GWO-CNN design yields parameter values almost identical to the calculated ones and significantly outperforms CNN without optimization. This demonstrates the robustness and efficiency of the proposed method.

Input Features (CNN)				CNN Trained Parameters			GWO-CNN Trained Parameters			Calculated Parameters		
1-4(lr)5-7(lr)8-10(lr)11-13 P_g (p.u.)	Q_g (p.u.)	V_t (p.u.)	X_{ext} (p.u.)	K_{cnn}	τ_1	τ_2	K_{cnn}	τ_1	τ_2	K^*	τ_1^*	τ_2^*
0.682	0.352	1.094	0.712	37.115	0.304	0.111	37.137	0.304	0.111	37.140	0.304	0.111
0.645	0.374	1.058	0.703	41.293	0.306	0.112	41.310	0.306	0.112	41.329	0.306	0.112
0.719	0.511	1.053	0.693	42.786	0.303	0.109	42.799	0.303	0.109	42.805	0.303	0.109
0.832	0.566	1.061	0.602	34.375	0.300	0.097	34.352	0.300	0.097	34.360	0.300	0.097
0.652	0.427	0.979	0.572	39.348	0.303	0.099	39.370	0.303	0.099	39.357	0.303	0.099
0.895	1.618	0.947	0.778	109.315	0.293	0.114	109.322	0.293	0.114	109.305	0.293	0.114
0.601	0.318	0.990	0.505	34.612	0.306	0.096	34.627	0.306	0.096	34.645	0.306	0.096
0.961	1.182	0.944	0.583	57.193	0.291	0.093	57.205	0.291	0.093	57.221	0.291	0.093
0.961	0.877	1.054	0.614	39.312	0.296	0.096	39.320	0.296	0.096	39.338	0.296	0.096
0.567	0.472	0.915	0.596	54.018	0.302	0.103	54.027	0.302	0.103	54.045	0.302	0.103

Table I. Ten representative operating scenarios

IX. Performance Assessment Through Case Studies

The effectiveness of the proposed Grey Wolf Optimizer (GWO)-assisted Convolutional Neural Network (CNN) based Power System Stabilizer (PSS) is examined through multiple dynamic operating scenarios. For comparison, three configurations are considered: (i) system without a stabilizer, (ii) system equipped with a conventional $\Delta\omega$-based PSS, and (iii) system with a Multi-

Band Power System Stabilizer (MBPSS). The analysis focuses on rotor speed and rotor angle deviations to assess the damping capability under transient disturbances. For the first case, nominal operating conditions of the Single-Machine Infinite Bus (SMIB) system are used, with the generator active power set to $P_g = 0.81$ p.u., reactive power $Q_g = 0.87$ p.u., terminal voltage $V_t = 1.014$ p.u., and external reactance $X_{ext} = 0.722$ p.u. A disturbance is introduced, and the response of the system is observed to evaluate the stabilizer performance. The optimized parameters provided by the GWO-CNN framework for this operating point are $\tau_1 = 0.292$ s, $\tau_2 = 0.107$ s, and stabilizing gain $K_{cnn} = 56.72$. The resulting rotor speed deviation is illustrated in Fig. 7, while the rotor angle variation is shown in Fig. 8. The results highlight that the proposed GWO-CNN-based PSS achieves faster damping and smaller oscillations than both the conventional $\Delta\omega$ stabilizer and the MBPSS, thereby offering significantly enhanced system stability.

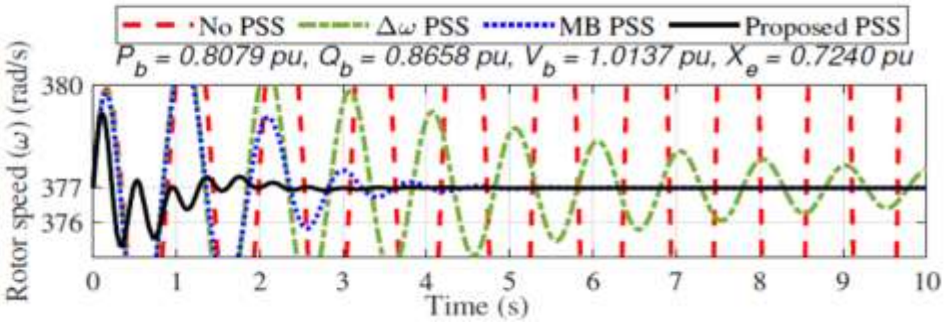

Fig. 7. Case I: Rotor speed deviation under nominal conditions

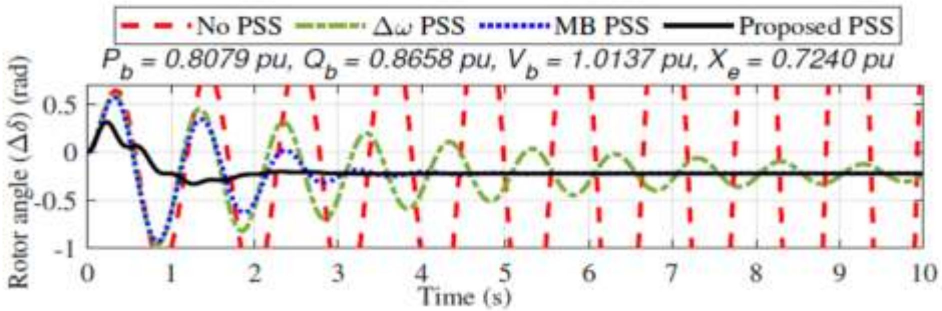

Fig. 8. Case I: Rotor angle deviation under nominal conditions

X. Conclusion

This study presents a Power System Stabilizer (PSS) design for damping low-frequency oscillations in a Single-Machine Infinite Bus (SMIB) system, where a Convolutional Neural Network (CNN) is employed with its hyperparameters optimally tuned through the Grey Wolf Optimizer (GWO). Using real-time operating data as inputs, the CNN predicts stabilizer settings while retaining the conventional lead–lag structure, ensuring compatibility with established control frameworks. Simulation outcomes demonstrate that the proposed GWO-CNN-based stabilizer achieves superior damping, improved dynamic stability, and faster settling when compared to conventional PSS approaches. Given its adaptability and learning capability, the method shows strong potential for extension to multi-machine networks and systems with high renewable penetration, making it a promising candidate for future real-time power system applications.

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