Design and Performance Analysis of Opposition based Whale Optimization Algorithm Tuned Power System Stabilizer for Multimachine Stability

By

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ABSTRACT

To build a power stabilizer and increase multimachine stability, a novel opposition based whale optimization algorithm (OWOA) is used in the current contribution. A conventional PSS with lead-lag compensator is considered for this work. OWOA fine-tunes the PSS's settings. The objective function utilised for tuning is the minimising of integral absolute error of speed deviations of generator rotors. Different time-domain simulation test cases are performed to validate the superior performance of the proposed PSS. Further, the performance of proposed PSS is compared with whale optimization algorithm (WOA) based PSS and conventional PSS. The obtained results certify the efficient performance of proposed OWOA based PSS for power oscillation damping.

Keywords: *Power oscillations; Whale optimization algorithm; opposition-based learning; power system stabilizer; 2-area 4-machine system.*

INTRODUCTION

The rise in demand for electricity has resulted in the extension and connectivity of previously established networks. The electricity system is influenced in a variety of ways by these interconnections. The rotor angle instability is one of the more noticeable phenomena that can occur inside these coupled systems [1]. Conventional power system stabilizers (CPSSs) are put to use to dampen out oscillations between areas of a system that are more likely to occur in interconnected systems. However, in order to achieve such accurate performance of CPSSs, a CPSS that has been designed correctly is required [2].

There are a number of papers available that point to the utilisation of optimization methods in the design of PSS with reference to power oscillation damping. It is discussed in [3], how the robust control theory can be applied to the process of designing a CPSS. An enhanced fuzzy logic power stability scheme designed to increase the stability of multimachine power systems is provided in [4]. In [5], CPSSs are designed in such a way to suppress electromechanical oscillations. In [6], the authors suggest creating a CPSS and a Static VAR Compensator (SVC) based on Shuffled Frog Leaping (SFL) and Chaos Particle Swarm Optimization (PSO) Algorithms to boost the stability of the power system. A coordinated design approach for CPSSs and automatic voltage regulators (AVRs) in a intensely linked system is presented here. in [7]. A new optimization technique based on the multi-objective genetic approach (MOGA) has been proposed in [8] with the aim of achieving the best coordinated selection of power system stabilizers (PSS) and flexible AC transmission systems (FACTS). The components of FACTS devices include a standard lead-lag damping controller built on a thyristor based controlled phase shifter (TCPS), static variable compensators (SVC), and a thyristor controlled series compensator (TCSC). A new field test developed to appropriately assess the PSSs' performance in reducing oscillations in a power station with multiple generators is discussed in in [9]. Using coordinated gain tuning and coordinated phase and gain tuning as examples, [10] demonstrates that conic programming is a highly effective method for resolving issues related to the creation of reliable power system stabilizers (PSS). According to [11], evolutionary algorithms can be utilized to create resilient multimachine power system stabilizers with the best multi-objective design. The power system in France now includes a robust coordinated PSS+AVR termed the "desensitized Four Loop regulator" which was built for the system and is currently in the process of being installed [12]. In [13], a multi-objective optimization model is provided for the goal of determining the feasible stability zone and the highest enduring disturbance rejection for a dynamic model of a small-signal power system with saturation nonlinearities and disturbance rejection. In [14], an innovative method to the optimal design of multimachine CPSSs that is based on an evolutionary algorithm is presented. An examination of the efficiency of CPSSs is presented taking into account a variety of system circumstances and operating loads in [15]. A CPSS that is based on tabu search (TS) is proposed in [16]. In [17], a method for simultaneously tuning modern CPSSs in multimachine power systems that is based on an algorithm called the Bacterial Foraging Algorithm (BFA) is described. Well-known bio-inspired algorithms include the bacterial foraging algorithm (BFA) and small-population-based PSO (SPPSO). To construct several optimum PSSs in two power systems simultaneously, [18] covers both of these. The proposed approach makes use of a Kalman filter as its foundation, and it is predicated on the system identification as presented in [19]. In [20], PSO algorithm has been modified to have tiny population is described in order to create the superior CPSSs. The scheme of an adaptive power system stabilizer by means of artificial neural network (ANN) is described in [21]. A pole placement method for power system stabilizers (PSS) and stabilizers based on thyristor controlled series capacitors (TCSC) has been published in [22] using the simulated annealing (SA) algorithm. The ideal locations and designs of sturdy multimachine power system stabilizer (PSSs) are presented in [23] using a genetic algorithm (GA). A new metaheuristic method called the bat search algorithm has been put forth in [24] for the best design of Power System Stabilizers (PSSs) in a multimachine setting. For the design of CPSSs in a multimachine power system, the Cuckoo Search (CS) algorithm is presented in [25]. For the purpose of reducing oscillations in power systems, a power system stabilizer (PSS) based on BFOA is proposed in [26]. In [27], a harmony search algorithm (HSA) is used to create a fuzzy logic power system stabilizer, aiming to establish the best balance between the input and output scaling factors of the fuzzy logic controller (FPSS). The damping factor and damping ratio are typically used as restrictions in the mathematical representation of the process of fine-tuning the PSS parameters for a multimachine power system, as shown in [28].

In this study, a PSS is created using the opposition-based whale optimization algorithm (OWOA) to reduce power oscillations in multimachine systems. A successful optimization algorithm is the whale optimization algorithm (WOA) [29]. The minimization of integral time absolute errors of speed deviations of generator rotors is taken into account as a fitness function for setting PSS parameters. System with suggested PSS performance is validated by comparison to system with WOA-based PSS, system with CPSS, and system without PSSs. Under various operating situations, the suggested PSS's effective performance is investigated. It is discovered that the suggested OWOA-based PSS outperforms other PSSs.

1. Structure of PSS

Conventionally, phase compensation approach is adopted in design of CPSS. In this work, the same approach is adopted. The transfer function block of CPSS is depicted in Fig. 1. The basic blocks in CPSS are gain block, washout block, lead-lag phase compensation block and a limiter. Rotor speed deviation is given as input to CPSS which goes into gain block with gain K_{gain}.

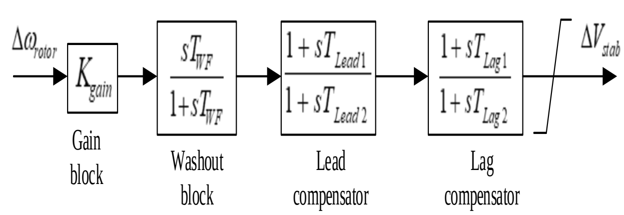


Fig. 1 Block diagram of classical PSS.

The signal from gain block enters washout block with washout constant $T_{WF} = 10\ s$. From washout block, the signal passes through phase compensation blocks with time constants T_{Lead1}, T_{Lead2}, T_{Lag1} and T_{Lag1}.

A stabilizing signal ΔV_{stab} is obtained after phase compensation block. This stabilizing signal is used by exciter of generator to damp out power oscillations. During transient operation, CPSS should stabilize the system.

2. System under study

A two-area four machine that sees widespread use. The testing system used by Kundur is investigated in this work. As can be seen in Fig. 2 a MATLAB model of the system has been developed. The testing system is made up of two completely symmetrical areas that are connected to one another by two 230 kV lines that are each 220 km in length. It was developed with a specialized focus to learn about low frequency fluctuations in linked systems [30, 31]. There are two identical round rotor generators at each location that each have a rating of 20 kV/900 MVA. The parameters [30, 31] for the synchronous machines are the same, with the exception of the inertias, which in region 1 are H = 6.5s and in region 2 are H = 6.175s[30, 31]. In addition, it is presumed that the speed regulators in all thermal plants will be identical, and fast static exciters will have a gain of 200 [30, 31]. The load is spread among the areas as constant impedances, with area 1 serving as the source of 413 MW of power that is exported to area 2. It is possible for generation and transmission losses to differ depending as per the level of detail in the representation of the line and the generator.

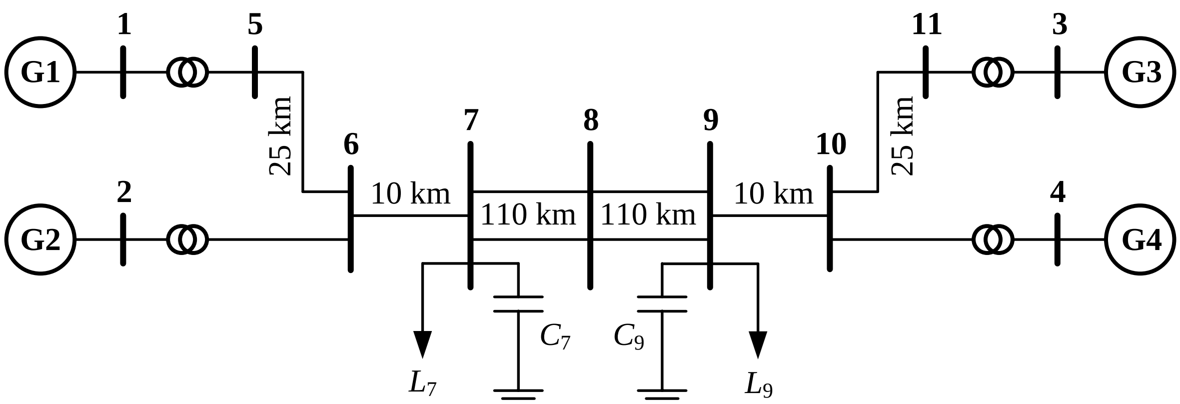


Fig. 2. Single line diagram of Kundur system.

3. Problem formulation

To obtain optimal parameters of CPSS, the minimization of integral time-multiplied absolute errors (ITAE) of the speed deviations of t rotors of generators is considered as the fitness function. The fitness function J is expressed in the following manner:

$$J = \int_{t=0}^{T_S} \left(\Delta\omega_{rotor,i}\right) \cdot t \cdot dt \tag{1}$$

where, $\Delta\omega_{rotor,i}$ is the speed deflection in ith generator and $i = 1,2,3\ and\ 4$. T_S is the total simulation time. The fitness function J expressed in (1) is minimized considering the following parameter constraints. The constraints are expressed as follows:

$$K_{gain}^{min} \leq K_{gain} \leq K_{gain}^{max} \tag{2}$$

$$T_{Lead1}^{min} \leq T_{Lead1} \leq T_{Lead1}^{max} \tag{3}$$

$$T_{Lead2}^{min} \leq T_{Lead2} \leq T_{Lead2}^{max} \tag{4}$$

$$T_{Lag1}^{min} \leq T_{Lag1} \leq T_{Lag1}^{max} \tag{5}$$

$$T_{Lag2}^{min} \leq T_{Lag2} \leq T_{Lag2}^{max} \tag{6}$$

where, K_{gain} is the gain of PSS and $T_{Lead1}, T_{Lead2}, T_{Lag1}, and\ T_{Lag2}$ are the coefficients of phase compensation block of PSS. $'max'$ and 'min' superscripts represent maximum and minimum values of the parameters.

As a result, the primary objective in tuning the parameters of PSS is to achieve the lowest possible value of the fitness function J defined in (1) subjected to the system constraints expressed in (2), (3), (4), (5), and (6). OWOA is proposed as a answers to the challenges of tuning the parameters of PSS within the scope of this work.

4. Opposition-based whale optimization algorithm

4.1 Overview of whale optimization algorithm

The WOA method, a population-based meta-heuristic optimization technique, was inspired by humpback whales' bubble-net feeding habit. It is a relatively novel algorithm that has been proposed in [29] and is utilized to get answers of a variety of optimization problems [32-36]. The three basic stages of this procedure are encircling the prey, spiral bubble-net feeding behavior, and hunting for prey. The mathematical model that supports each phase is described here.

4.1.1 Encircling prey

It is widely believed that whales have the ability to find their prey before circling it. All whales make an effort to modify their positions in order to get closer to the prey since they believe it to be the best candidate solution. This behavior can be understood mathematically by looking at the following representation:

$$\vec{P}_{encircle} = \left|\vec{F}_{encircle} \cdot \vec{X}_n^{best} - \vec{X}_n\right| \quad (7)$$

$$\vec{X}_{n+1} = \vec{X}_n^{best} - \vec{B}_{encircle} \cdot \vec{P}_{encircle} \quad (8)$$

where $\vec{X}_n^{best}$ is the best position vector in nth iteration. $\vec{B}_{encircle}$ and $\vec{F}_{encircle}$ are coefficient vectors. $\vec{X}_n$ and $\vec{X}_{n+1}$ are the position vectors in nth and $(n+1)$th iterations, respectively.

The vectors $\vec{B}_{encircle}$ and $\vec{F}_{encircle}$ are computed as

$$\vec{B}_{encircle} = 2\vec{e} \cdot \vec{\varepsilon} - \vec{e} \quad (9)$$

$$\vec{F}_{encircle} = 2 \cdot \vec{\varepsilon} \quad (10)$$

where $\vec{e}$ is linearly decreasing from 2 to 0 with each iteration and $\vec{\varepsilon}$ is a random number in the range $[0,1]$.

4.1.2 Bubble-net feeding behavior

The spiral updating position and the shrinking encircling mechanism form the basis for this phase's methodology. The feeding behavior is achieved in the shrinking encircling mechanism by lowering the value of $\vec{e}$ defined as in (9). Due to the dependence of $\vec{B}_{encircle}$ on $\vec{e}$, $\vec{B}_{encircle}$ will also decrease as $\vec{e}$ decreases. Therefore, it can be claimed that $\vec{B}_{encircle}$ is a value chosen at random from the interval $[-\vec{e}, \vec{e}]$. The position of the new candidate solution can be defined as falling somewhere between the position of the currently best solution and the position it originally occupied if the random values for $\vec{B}_{encircle}$ are set in the interval [-1,1].

In the spiral updating position phase, the mimicry of helix-shaped movements made by whales is modelled by a spiral mathematical equation, which can be represented as follows:

$$\vec{L}_{spiral} = \left|\vec{X}_n^{best} - \vec{X}_n\right| \quad (11)$$

$$\vec{X}_{n+1} = \vec{L}_{spiral} \cdot (\exp)^{bl} \cdot cos(2 \cdot \pi \cdot l) + \vec{X}_n^{best} \quad (12)$$

where the $\vec{L}_{spiral}$ is distance between the whale and its prey. A constant called b is used to specify the spiral's shape, and l can be any random number between [-1,1].

In addition, while the optimization process is being carried out, it is assumed that there is an equal likelihood of a spiral updating position phase and an equal probability of a shrinking encircling mechanism. If ρ is any random number between 0 and 1, then the following is one way to define the whales' most recent position vector.

$$\vec{X}_{n+1} = \begin{cases} \vec{X}_n^{best} - \vec{B}_{encircle} \cdot \vec{P}_{encircle} & \text{if } \rho < 0.5 \\ \vec{L}_{spiral} \cdot (exp)^{bl} \cdot cos(2 \cdot \pi \cdot l) + \vec{X}_n^{best} & \text{if } \rho \geq 0.5 \end{cases} \quad (13)$$

The solutions that are deemed to be superior will move on to the next phase.

4.1.3 Searching for prey

During this phase, whales looks for prey in a random manner while taking into account the positions of one another. In order to carry out this phase of the process, the value of $\vec{B}_{encircle}$ is changed so that it is either less than -1 or greater than 1, which compels the agents to advance further inside the search space. A search on a global scale is conducted as a result. The following is an illustration of how it is represented:

$$\vec{P}_{encircle} = \left|\vec{F}_{encircle} \cdot \vec{X}_n^{rand} - \vec{X}_n\right| \quad (14)$$

$$\vec{X}_{n+1} = \vec{X}_n^{rand} - \vec{B}_{encircle} \cdot \vec{P}_{encircle} \quad (15)$$

where $\vec{X}_n^{rand}$ is a position vector taken at random from the group that is currently being used. The solutions that are judged to be superior are chosen and brought forward to the subsequent iteration. As a result, the procedure in its entirety is carried out again and again until the termination criteria are fulfilled.

4.2 Opposition based learning

Opposition based learning is introduced in [37]. In this type of learning, the fitness functions are evaluated on randomly generated solution and on opposite number solution and whichever is produces the minimum value for a minimization problem is chosen. Mathematically, it is represented as

$$x_{new} = x_{old} \text{ if } f(x_{old}) < f(x_{opposite}) \tag{20}$$

where x_{old} and $x_{opposite}$ are the old solution and opposite solution.

The opposite number or solution $x_{opposite}$ can be obtained by

$$x_{opposite} = m + n - x_{old} \tag{21}$$

where x_{old} lies in the range $[m, n]$.

4.3 Opposition based whale optimization algorithm

The OWOA is proposed in this work where the initial random solution will be replaced by opposite number solution. Rest of the method of OWOA will remain same as WOA.

4.4 Implementation of OWOA to the problem

The problem of tuning the parameters of PSSs is addressed by applying OWOA as a solution. The following is enumeration of the various steps that were involved in its implementation:

Step1: Read the data from the system and adjust the algorithm control parameters, like the maximum number of iterations, the population size and the boundary conditions.

Step 2: Generate the initial population of the solution by selecting individuals at random from the search space.

Step 3: Generate opposite number solution from initial randomly generated solution.

Step 4: Determine the optimal solution after analyzing the objective function.

Step 5: It is necessary to update the solution in accordance with the updating equation.

Step 6: Choose the more effective solutions to take part in the following iteration.

Step 7: Proceed to step 3 until one of the criteria for terminating the process has been satisfied.

5. Simulation results and discussion

The results of the simulation as well as a discussion of them are presented in this section. When performing the simulation, both the large-signal and the small-signal stability test cases are taken into consideration. The system that has been looked at is a four-machine system with two-area. To tune the parameters of power system stabilizers, OWOA algorithm is applied. For each and every test case, a total of one hundred iterations and a population size of twenty are taken into consideration. On the MATLAB platform, both the modelling of the system and the implementation of the algorithms are carried out. OWOA has the additional benefit of having fewer algorithm-specific parameters, which is a distinct advantage. The boundary conditions of parameters of PSS are shown in Table 1.

Table 1. Boundary conditions of parameters of PSS

Parameters	K_{gain}	T_{Lead1}	T_{Lead2}	T_{Lag1}	T_{Lag2}
Range	1 - 50	0.01 – 0.01	0.01 – 0.1	1 - 10	1 - 10

Two test examples are taken into consideration for fine-tuning PSS's parameters. The first case evaluates the robustness of the proposed PSS under the stability of small signals. The second case evaluates how well the proposed PSS performs in terms of its large-signal stability. In each scenario, the tuned parameters along with the value of the objective function are tabulated for OWOA-based PSS and WOA-based PSS, respectively, and compared with one another. Simulations in the time domain are presented in order to demonstrate how the proposed PSSs improve the overall functionality of the system.

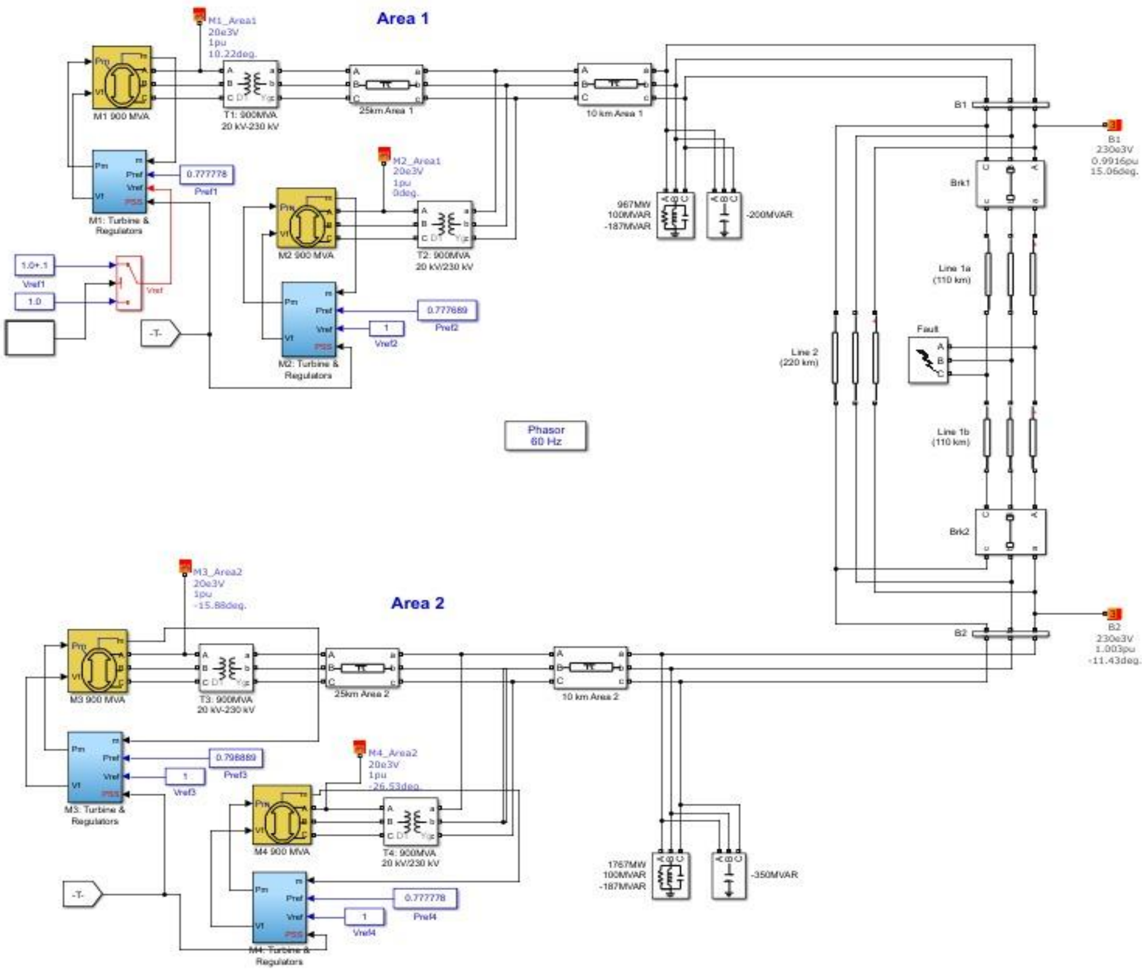


Fig.3 Simulink diagram of the studied system.

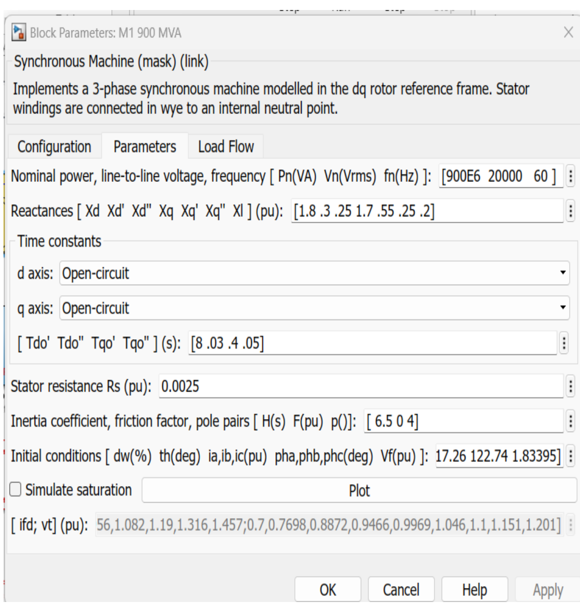


Fig. 4 Parameters of generators

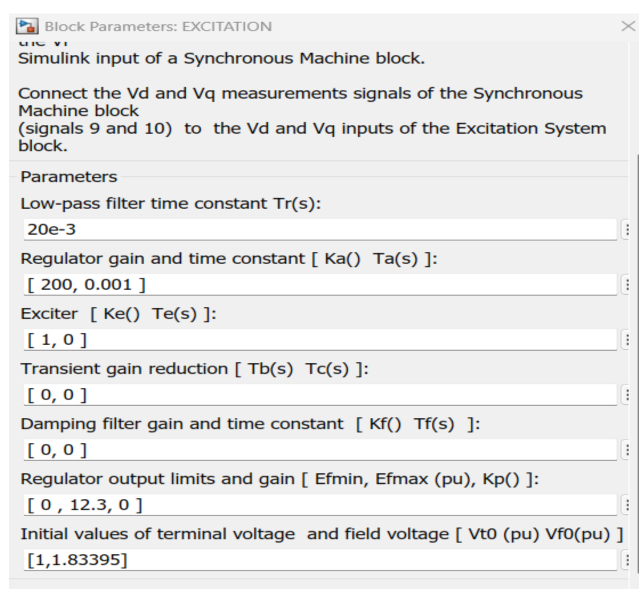


Fig. 5 Parameters of excitation system

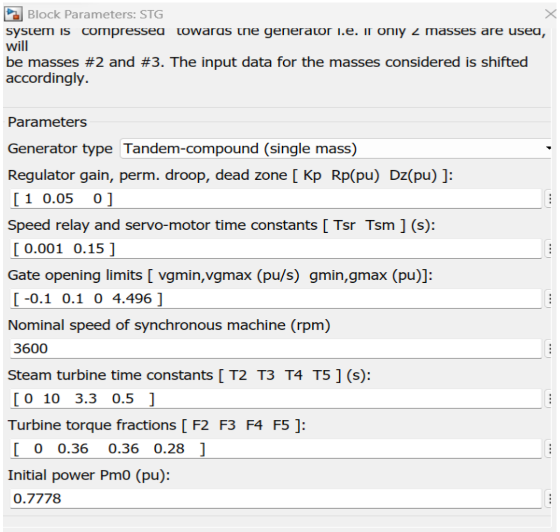


Fig. 6 Parameters of steam turbine

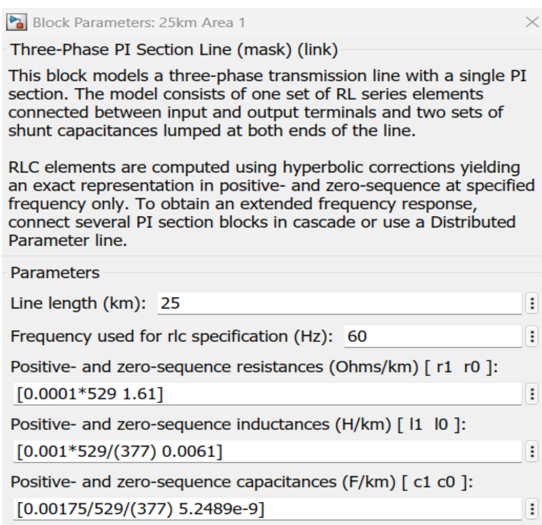


Fig. 7 Parameters of transmission line

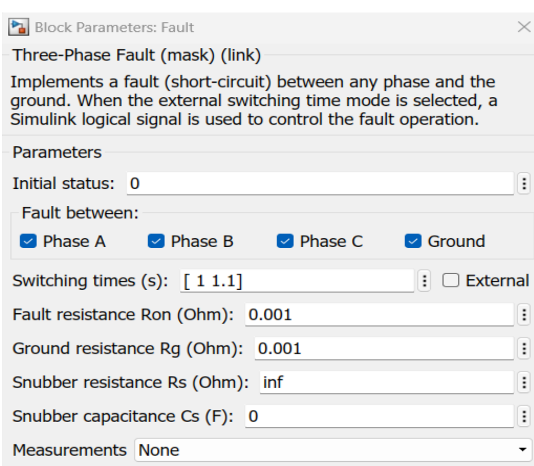


Fig. 8 Parameters of three-phase fault

5.1 Small-signal stability

The small-signal stability assessment of the system is carried out so that the performance of the proposed PSS can be demonstrated. It is assumed that there will be an increase of 10% in the voltage reference of generator G1 that will be applied at 1 s and maintained for 0.2 s. In this particular scenario, the PSS parameters are fine-tuned with the assistance of OWOA and WOA. Table 2 displays the tabulated results of the study. The table shows that the minimum value of objective function J is found to be **0.0015**, which is obtained from OWOA. This information can be seen by looking at the table. As a result, we can conclude that the performance of a PSS based on OWOA is superior to the PSS based on WOA.

Table 2. Optimal parameters for case of small-signal stability

Values	WOA based PSS	OWOA based PSS
J	0.0024	**0.0015**
K_{gain}	50	50
T_{Lead1}	0.0832	0.0100
T_{Lead2}	0.0562	0.0169
T_{Lag1}	7.4744	10
T_{Lag2}	5.0101	7.2166

The performance of system with proposed PSS is demonstrated through time-domain simulations, in comparison to the system without PSSs and the system with conventional PSSs. In Fig. 9 rotor-angle discrepancies are displayed. It is evident from the figure that the the deviations are reaching steady-state if OWOA based PSS is used in the system. Further, proposed PSS is found to be better than WOA based PSS and CPSS. The system without PSS becomes unstable in case of small disturbance in reference voltage at terminal of generator G1. The rotor speed variations after the disturbance are depicted in Fig. 10. The same aforementioned inference can be derived from the figure results.

Therefore, it can be concluded here that OWOA based PSS is performing efficiently than others in context of power oscillation damping in case of small signal stability

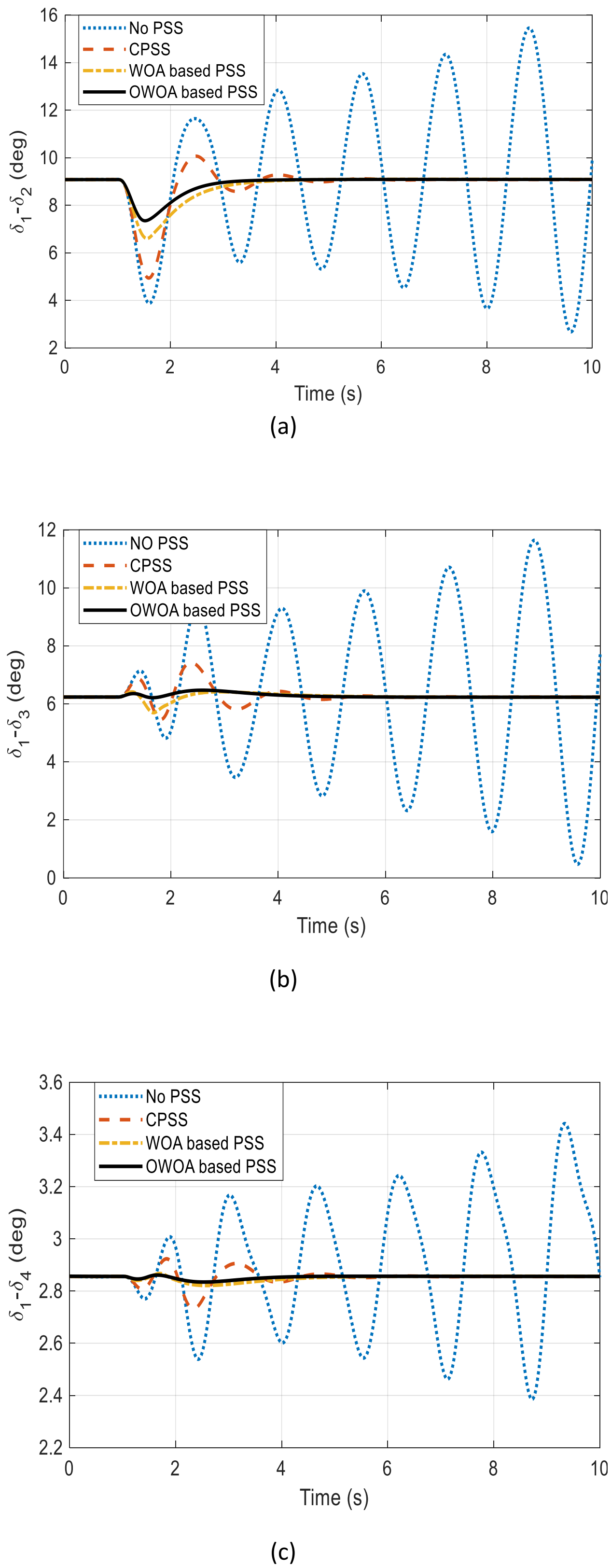
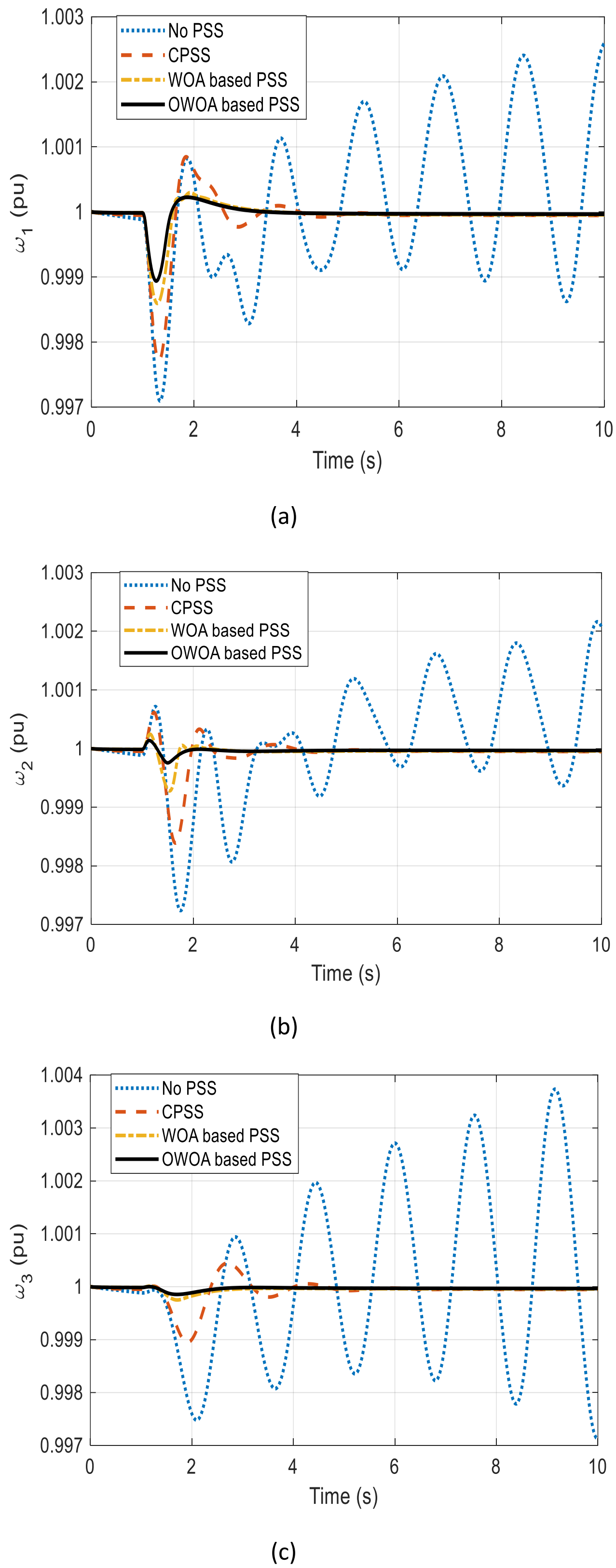
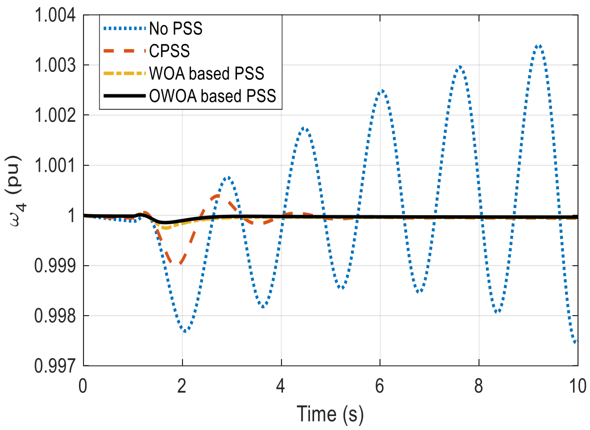


Fig. 9. Rotor-angle deviations for case of small-signal stability. (a) $\delta_1 - \delta_2$ (b) $\delta_1 - \delta_3$ (c) $\delta_1 - \delta_4$.





(d)

Fig. 10. Rotor speed for case of small-signal stability. (a) ω_1 (b) ω_2 (c) ω_3 (d) ω_4.

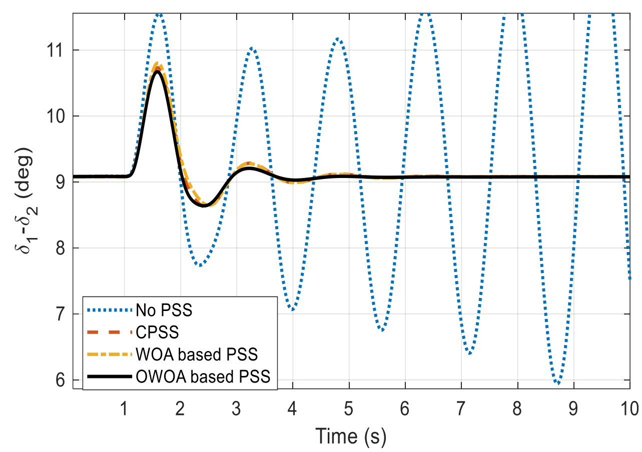
5.2 Large-signal stability

In this case, the performance of the proposed PSS is analyzed to determine whether or not the system stabilizes after any significant disturbances. For the purpose of simulation, a three-phase fault to the ground is introduced on the middle of the line 7 - 8 at 1 second and is cleared after 0.1 second. In this particular scenario, the PSS parameters are fine-tuned with the assistance of OWOA and WOA. Table 3 displays the tabulated results of the study. The table shows that the minimum value of objective function J is found to be **0.0032** which is obtained from the OWOA. This can be seen by looking at the table. As a result, it can be concluded that the performance of a PSS based on OWOA is superior to that of a PSS based on WOA.

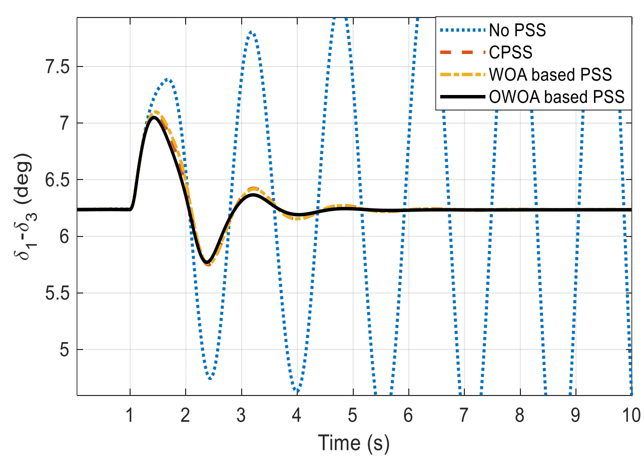
The performance of system with proposed PSS is demonstrated through time-domain simulations, in comparison to the performance of the system without PSSs and the system with conventional PSSs. In Fig. 11 rotor-angle discrepancies are displayed. It is evident from the figure that the deviations are reaching steady-state if OWOA based PSS is used in the system. Further, proposed PSS is found to be better than WOA based PSS and CPSS. The system without PSS becomes unstable in case of small disturbance in reference voltage at terminal of generator G1. The rotor speed variations after the disturbance are depicted in Fig. 12. The same aforementioned inference can be derived from the figure results. Therefore, it can be concluded here that OWOA based PSS is performing efficiently than others in context of power oscillation damping in case of large signal stability

Table 3. Optimal parameters for case of large-signal stability

Values	WOA based PSS	OWOA based PSS
J	0.0038	**0.0032**
K_{gain}	12.9485	10.0785
T_{Lead1}	0.0577	0.0912
T_{Lead2}	0.0634	0.0858
T_{Lag1}	5.4545	8.7230
T_{Lag2}	4.2469	4.0983



(a)



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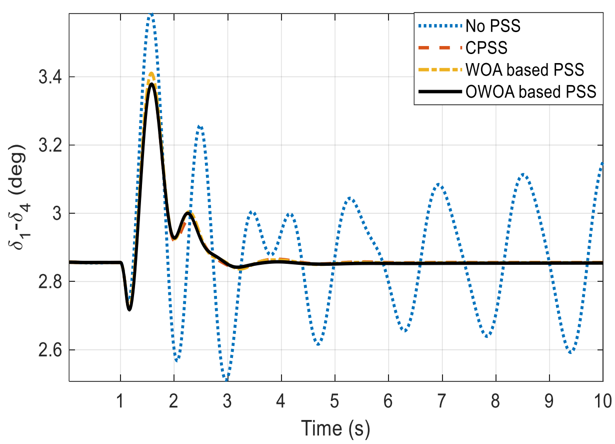
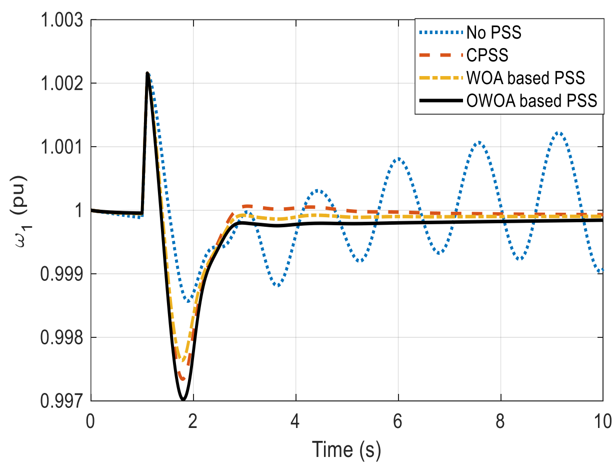
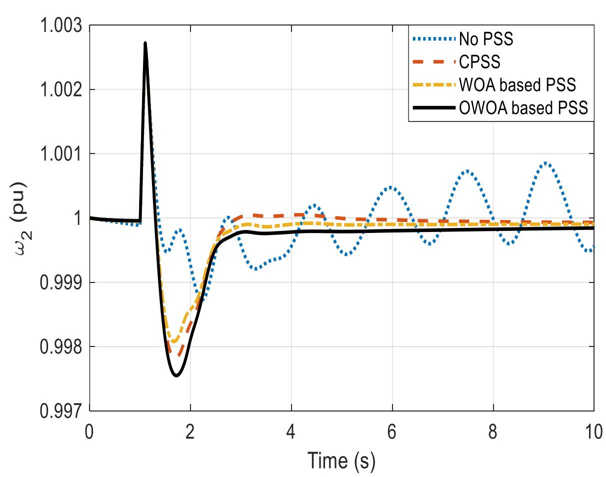


(c)

Fig. 11. Rotor angle deviations for case of large-signal stability. (a) $\delta_1 - \delta_2$ (b) $\delta_1 - \delta_3$ (c) $\delta_1 - \delta_4$.



(a)



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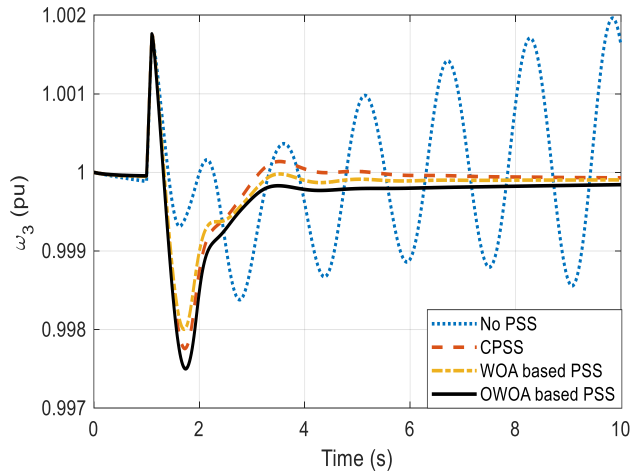

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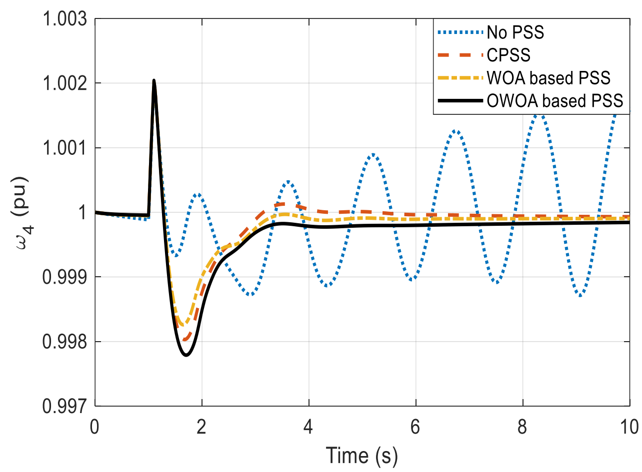

(d)

Fig. 12. Rotor speed deviations for case of large-signal stability. (a) ω_1 (b) ω_2 (c) ω_3 (d) ω_4.

6. Conclusion

In this work, the OWOA is used to tune the parameters of the CPSS for power oscillation damping. For the purpose of simulation, a widely used two-area four machine test system is utilized. The OWOA-based PSS is developed by attempting to minimize the integral errors caused by variations in rotor speed. For the purpose of evaluating how well the proposed OWOA-based PSS performs, two test cases consisting of small-signal and large-signal stability assessments are carried out. The results of a comparison between the performance of the proposed PSS and the performance of a WOA-based PSS validate the superior performance of the proposed PSS. When the system with proposed PSS is compared to the system with only CPSS and the system without PSS, one can draw the conclusion that the system with proposed PSS performs better than the systems with CPSSs and systems without PSSs based on the observations. Future research directions include the application of a hybrid optimization algorithm to tune the parameters of PSS in order to get better tuned values, the formulation of a multi-objective optimization problem in order to achieve better performance of the system under disturbances, the design of PSS for renewable integrated energy system using the proposed technique, and the testing of the performance of the proposed PSS on large power systems.

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