Indonesian Journal of Electrical Engineering and Computer Science
Vol. 8, No. 2, November 2017, pp. 382 ~ 390
DOI: 10.11591/ijeecs.v8.i2.pp382-390

PSS Based Angle Stability Improvement Using Whale Optimization Approach

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Abstract

This paper introduced a new swarm based optimization technique for tuning Power System Stabilizer (PSS) that attached to a synchronous generator in a single machine infinite bus (SMIB) system. PSS which is installed with Lead-Lag (LL) controller is introduced to elevate the damping capability of the generator in the low frequency mode. For tuning PSS-LL parameters, a new technique called Whale Optimization Algorithm (WOA) is proposed. This method mimics the social behavior of humpback whales which is characterized by their bubble-net hunting strategy in order to enhance the quality of the solution. Based on eigenvalues and damping ratio results, it is confirmed that the proposed technique is more efficient than Particle Swarm Optimization (PSO) and Evolutionary Programming (EP) in improving the angle stability of the system. Comparison between WOA, PSO and EP optimization techniques showed that the proposed computation approach give better solution and faster computation time.

Keywords: *Angle Stability, Damping Ratio, Power System Stabilizer, Particle Swarm Optimization, Whale Optimization Algorithm.*

1. Introduction

The excitation control of generators is among the important topics in the field of power system. A good excitation control is the best way to damp the oscillations and improve the angle stability of generators. Power system stabilizer (PSS) is widely used in order to improve the dynamic stability and damping the low frequency mode of the inter-area oscillation. Compared to Flexible Alternating Current Transmission Systems (FACTS) technologies, the proposed approach use less of heavy equipments, so that it is more cost-effective. Moreover, supplementary controllers designed for each FACTS device are not directly involved with electromechanical oscillations. As a result, the damping controller design is not as straightforward as those of the PSS [1-3,13,15].

In this study, a Lead-Lag (LL) controller is combined with PSS to give more sufficient control to the oscillations. For tuning the PSS-LL controller, three variables: lead compensator time constant, T_1, lag compensator time constant, T_3 and washout time constant, T_W are need to be optimized.

Optimization approaches are frequently chosen to tune variables of devices in solving power system stability problems. Among them are Evolutionary Programming (EP) [4,5], Particle Swarm Optimization (PSO) [6-8] and Bat algorithm (BAT) [15,16]. EP used biological evolution process in searching for an optimal solution. On the other hand, PSO is a technique that influenced by the behaviours of fish schooling and bird flocking. As a metaheuristic optimization technique similar to PSO, BAT optimization technique comprises the echolocation behavior of bats found in nature. A new nature-inspired meta-heuristic optimization algorithm called Whale Optimization Algorithm (WOA) is proposed [9,10]. This method mimics the social behavior of humpback whales which is characterized by their unique method of hunting known as the bubble-net feeding method. It brought better performance than PSO and EP in calculating the optimal solution.

This paper proposed a more effective approach in searching the best value of parameters for PSS-LL controller. All three fixed-gains of PSS-LL controller are determined using WOA. The objective is to produce the most stabilized technique in the shortest time.

Received July 30, 2017; Revised October 9, 2017; Accepted October 21, 2017

Three simulation cases were conducted to discuss the comparison of WOA-based optimization method with PSO and EP.

2. Problem Formulation

In this study, a single-machine-infinite-bus (SMIB) system is considered. The exciter of the generator is connected to the power system stabilizer with a lead-lag (PSS-LL) controller. PSS-LL controller regulates the current of the generator based on the speed deviation, $\Delta\omega$. As a result, the required damping torque can be channeled and damping out the oscillations.

Based on the SMIB system model with PSS-LL controller, a Phillips-Heffron based block diagram model which consists of Power System Stabilizer with Lead-Lag (PSS-LL) controller is designed. The block diagram model of PSS-LL controller is shown in Figure 1.

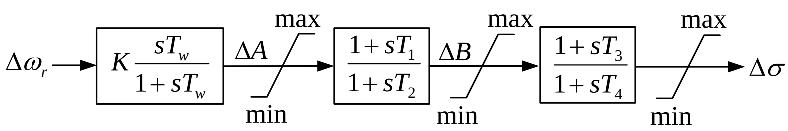


Figure 1. The block diagram model of PSS-LL controller

K_{st} is the stabilizer gain for PSS. T_w is the washout time constant. T_1 and T_2 are the time constant for the first phase compensation. T_3 and T_4 are the time constant for the second phase compensation.
The equations represent SMIB system installed with PSS-LL are as followed:

$$\frac{\Delta\omega}{\Delta t}=\frac{\Delta T_m-K_1\Delta\delta-K_d\Delta\omega_r-K_2\Delta E_q}{2H} \tag{1}$$

$$\frac{\Delta\delta}{\Delta t}=\omega_0\Delta\omega_r \tag{2}$$

$$\frac{\Delta E_q}{\Delta t}=-\frac{K_3K_4\Delta\delta+\Delta E_q-K_3\Delta v_f}{T_K} \tag{3}$$

$$\frac{\Delta v_f}{\Delta t}=-\frac{K_RK_5\Delta\delta+K_RK_6\Delta E_q+\Delta v_f+K_R\Delta\sigma}{T_R} \tag{4}$$

$$\frac{\Delta\sigma}{\Delta t}=-\frac{T_1T_3K_{st}}{2HT_2T_4}\left(K_d\Delta\omega_r+K_1\Delta\delta+K_2\Delta E_q\right)-\frac{1}{T_4}\left(\Delta\sigma-\Delta v_1\right)+\frac{T_3}{T_2T_4}\left(1-\frac{T_1}{T_W}\right)\Delta v_2 \tag{5}$$

$$\frac{\Delta v_1}{\Delta t}=-\frac{T_1K_{st}}{2HT_2}\left(K_d\Delta\omega_r+K_1\Delta\delta+K_2\Delta E_q\right)+\frac{1}{T_2}\left(1-\frac{T_1}{T_W}\right)\Delta v_2 \tag{6}$$

$$\frac{\Delta v_2}{\Delta t}=-\frac{K_{st}}{2H}\left(K_d\Delta\omega_r+K_1\Delta\delta+K_2\Delta E_q\right)-\frac{1}{T_W}\Delta v_2 \tag{7}$$

T_m is the mechanical torque, H is the inertia constant, K_D is the damping torque coefficient, K_R and T_R are the circuit constant and time constant of the exciter oscillation system, respectively. ω_0 is equal to $2\pi f_0$. The K constants i.e. K_1, K_2, K_3, K_4, K_5, K_6 and T_K are represent the dynamic characteristics of the system model. Detail calculation of parameters K_1, K_2, K_3, K_4, K_5 and K_6 can be found in [11].

Based on (1) - (7), a state-space form is developed as follows:

$$\dot{X}_{PSS} = A_{PSS} \cdot X_{PSS} + B_{PSS} \cdot U \tag{8}$$

$$X_{PSS} = [\Delta\omega_r \quad \Delta\delta \quad \Delta E_q \quad \Delta v_f \quad \Delta\sigma \quad \Delta v_1 \quad \Delta v_2]^T \tag{9}$$

$$U = \Delta T_m \tag{10}$$

where *X* and *U* are the state vector and input signal vectors, respectively. *A* and *B* are matrices of real constants and variables with suitable dimensions.

In this paper, the value of washout time constant, T_w, first phase compensation time constant, T_1 and second phase compensation time constant, T_3 are kept within specified limits. The value of T_2 and T_4 are chosen equal to the value of T_1 and T_3, respectively. The WOA algorithm is proposed to calculate the optimal computation of the PSS-LL controller parameters. The SMIB systems parameters are shown in Table 1. Details are explained in [11].

Table 1. The Parameters for SMIB and PSS System

Components	List of Parameters
Generator	H = 2.0, T_{d0}' = 8.0, X_d = 1.81, X_q = 1.76, X_d' = 0.30, R_a = 0.003, K_{sd} = K_{sq} = 0.8491, E_t = 1.0 ∠ -36°
Transmission Line	R_e = 0.0, X_e = 0.65, X_L = 0.16
Exciter and PSS	K_R = 200, T_R = 0.05, K_{st} = 9.5

3. Computational Intelligence Methods

In this study, the proposed WOA is compared with EP and PSO in order to highlight their merit. The algorithms for all methods are discussed below.

3.1 Evolutionary Programming

In the EP algorithm, the population has *n* candidate solutions with each candidate solution is an *m*-dimensional vector, where *m* is the number of optimized parameters. The EP algorithm can be described as:

a) Step 1 (Initialization): Generation counter *i* is set to 0, and generate *n* random solutions (x_k, k=1,…,n). The k^{th} trial solution x_k can be written as x_k=[p_1,…,p_m], where the l^{th} optimized parameter p_l is generated by random value in the range of[p_l^{min}, p_l^{max}] with uniform probability. Each individual is evaluated using the fitness function *J*. In this initial population, the maximum value of fitness function J_{max} will be searched; the target is to find the best solution x_{best} with objective function J_{best}.
b) Step 2 (Mutation): Each parent x_k produces one offspring x_{k+n}. Each optimized parameter p_l is perturbed by a Gaussian random variable $N(0, \sigma_l^2)$. The standard deviation σ_l specifies the range of the optimized parameter perturbation in the offspring. σ_l equation is as follows:

$$\sigma_l = \beta \times \frac{J(x_k)}{J_{\max}} \times \left(p_l^{\max} - p_l^{\min}\right) \tag{11}$$

where β is a scaling factor, and $J(x_k)$ is the objective function of the trial solution x_k. The value of optimized parameter will be set at certain limit if any value violates its specified range. The offspring x_{k+n} can be described as:

$$x_{k+n} = x_k + \left[N(0, \sigma_1^2), \ldots, N(0, \sigma_m^2)\right], \quad (k=1,\ldots,n) \tag{12}$$

c) Step 3 (Statistics): The minimum objective function J_{min} and the maximum objective function J_{max} of all individuals are calculated.
d) Step 4 (Update the best solution): If J_{max} is smaller than J_{best}, go to Step 5, or else, update the best solution, x_{best}. Set J_{max} as J_{best}, and go to Step 5.
e) Step 5 (Combination): All members in the population x_k are combined with all members from the offspring x_{k+n} to become *2n* candidates. These individuals are then ranked in descending order, based on their objective function as their weight.
f) Step 6 (Selection): The first *n* individuals with higher weights are selected along with their objective functions as parents of the next generation.
g) Step 7 (Stopping criteria): The search process will be terminated if it reaches the maximum number of generations or the value of (Jmax - Jmin) is very close to 0. If the process is not terminated, the generation will be set to i=i+1 and algorithm will start again from Step 2.

3.2 Particle Swarm Optimization

Particle Swarm Optimization (PSO) is similar to EP, an evolutionary based optimization technique, which imitates the behaviour of birds flocking and fish schooling. In this paper, the PSO algorithm works as follows:

a) Step 1 (Initialization): The velocity v_i and position x_i of N particles ($i=1,\ldots,N$) are randomly created to form initial population. Similar to EP, each particle is evaluated using the objective function J. In this initialization process, J_i is set as personal best objective function $J_{i,p}$ for *i*th particle. The maximum objective function of all particles J_{max} is set as global best objective function J_g. The position x_i for $J_{i,p}$, J_{max} and J_g is set as personal best position p_i, position with maximum objective function p_m and global best position g, respectively.
b) Step 2 (Update the velocity and positions): At *j*th iteration, the velocity and position of *i*th particle is updated according to the following equations:

$$v_i(j) = \omega v_i(j-1) + c_1 r\{p_i(j-1) - x_i(j-1)\} + c_2 r\{g(j-1) - x_i(j-1)\} \quad (13)$$

$$x_i(j) = v_i(j) + x_i(j-1) \quad (14)$$

where, ω is the inertia weight, c_1 and c_2 are acceleration coefficients, and r is random function in the range [0,1].
c) Step 3 (Calculate objective functions): The new J, J_{max} and the minimum objective function of all particles J_{min} are calculated.
d) Step 4 (Update the best positions): p_i and g are updated when the following conditions are met:
- If J_i is bigger than $J_{i,p}$, set J_i as $J_{i,p}$, and set x_i as p_i. Else, the value of $J_{i,p}$ and p_i are maintain.
- If J_{max} is bigger than J_g, set J_{max} as J_g, and set p_m as g. Else, the value of J_g and g are maintain.

e) Step 5 (Stopping criteria): The search process will be terminated if it reaches the maximum number of generations or the value of (J_{max} - J_{min}) is very close to 0. If the process is not terminated, the iteration will be set to $j=j+1$ and algorithm will start again from Step 2.

3.3 Whale Optimization Algorithm

Whale Optimization Algorithm (WOA) is a novel nature-inspired meta-heuristic optimization algorithm proposed by Seyedali Mirjalili and Andrew Lewis in 2016, which mimics the social behavior of humpback whales. The modelling of this algorithm includes three operators simulate the search for prey (exploration phase), the encircling prey, and the bubble-net foraging (exploitation phase). In this paper, the WOA works as follows:

a) Step 1 (Initialization): The whale position x_i of N *solution* ($i=1,\ldots,N$) are randomly created to form initial whale population. Similar to EP, each whale is evaluated using the objective function J. In this initialization process, J_i is set as personal best objective function $J_{i,p}$ for ith whale. The maximum objective function of all whales J_{max} is set as best objective function J_{best} and the whale position at J_{best} is set as best position x_{best}.

b) Step 2 (Update positions): x_i is updated when the following conditions are met:

- If iteration j is odd number and (J_{max} - J_i) < 0.1, update the current whale position x_i by the following equation:

$$x_i(j) = x_{best} + A \cdot (C \cdot x_{best} - x_i(j-1)) \tag{15}$$

where A is the inertia weight, C are random functions in the range [0,1]. This phase is called encircling prey. In this phase, WOA assumes that the current best position x_{best} is the target prey or close to the optimum.

- If iteration j is odd number and (J_{max} - J_i) ≥ 0.1, search average position for the current whale position x_i by the following equation:

$$x_i(j) = x_{average} + A \cdot (C \cdot x_{average} - x_i(j-1)) \tag{16}$$

This phase is called exploration phase. In this phase, the search agents are forced to move far away from the best whale position.

- If iteration j is even number, update the current whale position x_i by the following equation:

$$x_i(j) = x_{best} + (C \cdot x_{best} - x_i(j-1)) \cdot e^{bl} \cdot \cos(2\pi l) \tag{17}$$

where b is a constant, l is a random number in [−1,1].This phase is called exploitation phase. This equation is created between the position of whale and prey to mimic the helix-shaped movement of humpback whales.

c) Step 3 (Calculate objective functions): The new J, J_{max} and the minimum objective function of all whales J_{min} are calculated.

d) Step 4 (Stopping criteria): The search process will be terminated if it reaches the maximum number of generations or the value of (J_{max} - J_{min}) is very close to 0. If the process is not terminated, the iteration will be set to $j=j+1$ and algorithm will start again from Step 2.

3.4 Fitness Equation

The implementation of PSS-LL controller in the SMIB system will accelerate the oscillations damping and minimize the power angle deviation after a disturbance. In this paper, a fitness equation based on the combination of minimum damping ratio ξ_{min} and maximum damping factor σ_{max} effectiveness has been formulated as follows [12-14]:

$$J = \rho_2 \cdot \xi_{\min} + \rho_2 \cdot \sigma_{\max}\ ,\ \xi_i \in \xi_{EM}\ ,\ \sigma_i \in \sigma_{EM} \tag{18}$$

$$\xi = -\frac{\sigma_i}{\sqrt{\sigma_i^{\ 2} + \omega_i^{\ 2}}}\ ,\sigma_i \in \sigma_{EM} \tag{19}$$

ρ_1 and ρ_2 are random function in the range [0,1] attached to ξ_{min} and σ_{max}, respectively in order to tune the percentage of both indicators. σ_i and ω_i are respectively the real and imaginary part of the i^{th} eigenvalue.

With the optimization of σ, the system poles are pushed further to the left of the imaginary, $j\omega$ axis. Simultaneously, the optimization of ξ will decrease the value of $|j\omega|$, so that the region of the eigenvalues on the complex s-plane will overall shift towards the real, σ axis. The combination of both effects can be showed as a triangle-shaped sector on the complex s-plane. Figure 2 shows the regions of eigenvalues on the complex s-plane, before and after optimization process.

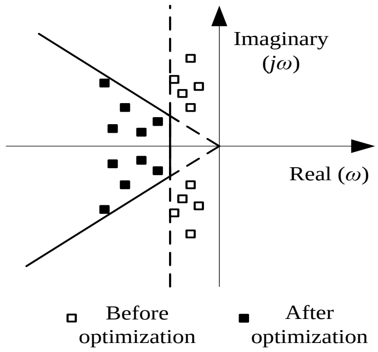


Figure 2. Comparison of eigenvalue areas on the complex s-plane (with and without *J*)

Therefore, the design problem can be formulated as: Maximize *J*
This is subject to

$$T_W^{max} \le T_W \le T_W^{min},$$
$$T_1^{max} \le T_1 \le T_1^{min},$$
$$T_3^{max} \le T_3 \le T_3^{min}$$

Here, T_w, T_1 and T_3 are optimized by EP, PSO and WOA approach. The fitness values and parameters involved in these three techniques are tabulated in Table 2.

Table 2. The Fitness Values and Parameters for EP, PSO and WOA Algorithms

Methods	EP	PSO	WOA	Fitness Values
List of Parameters	β=0.05	$c_1 = c_2 = 0.5$, $\omega_{max} = 0.09$, $\omega_{min} = 0.04$	$A = 0.9$, C = 1, $b = 1$, $l = 0.25$	$\rho_1 = 0.5$, $\rho_2 = 0.5$

4. Results and Discussion

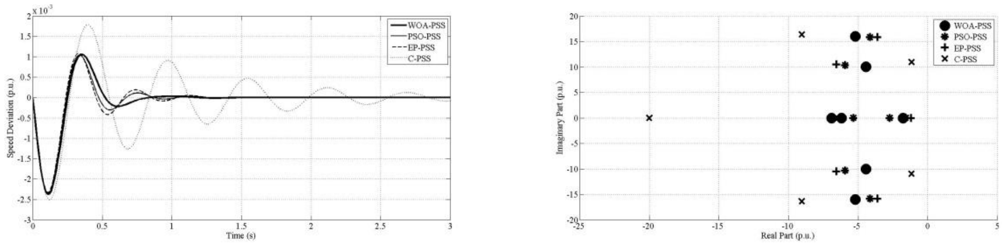
In this paper, simulation studies of a PSS-LL based SMIB power system are carried out in MATLAB environment. Three parameters: the value of washout time constant, T_w, first phase compensation time constant, T_1 and second phase compensation time constant, T_3 are optimized until maximum value of the fitness equation *J* is defined.

In this study, the performance of system with conventional PSS-LL system (C-PSS) is compared to PSS-LL system optimized by EP (EP-PSS), PSS-LL system optimized by PSO (PSO-PSS) and PSS-LL system optimized by WOA (WOA-PSS). Simulated loading conditions are tabulated in Table 3. Following three different loading conditions are simulated:

a) Case 1 (P = 0.5 p.u., Q = 0.2 p.u.)
b) Case 2 (P = 0.7 p.u., Q = -0.2 p.u.)
c) Case 3 (P = -0.2 p.u., Q = 0.75 p.u.)

The response of speed deviation for Case 1 is shown in Figure 3(a). The system with C-PSS is poorly damped and becomes stable for more than 3 seconds. On the other hand, the implementation of PSS in other three systems is improving the damping capability. From the speed response, its shows that WOA-PSS manage to deliver the fastest and smoothest damping performance, followed by PSO-PSS and EP-PSS.

From the eigenvalues perspectives, WOA is the most sufficient approach in shifting the eigenvalues further to the left-hand side of $j\omega$ axis, as well as towards σ axis at the loading condition compared to other three methods. It also shows that C-PSS have two eigenvalues that place near to the left-hand side of the $j\omega$ axis, indicate that the system is the most less stable. The regions of eigenvalues location in complex s-plane for all four techniques in Case 1 are shown in Figure 3(b).



(a) Speed response (b) Complex s-plane

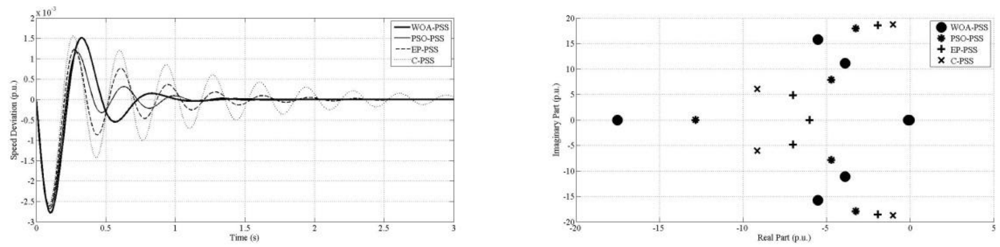
Figure 3. Speed response and complex s-plane for Case 1

Table 4. Comparison of C-PSS, EP-PSS, PSO-PSS and WOA-PSS System for Case 1

Type	T_W	T_1	T_3	J	ξ_{min}	σ_{max}	N_i
C-PSS	10	10	10	0.6319	0.1051	1.1588	-
EP-PSS	0.8753	0.1487	0.6008	0.7115	0.2231	1.2000	15
PSO-PSS	0.4117	0.1875	0.6358	0.9126	0.2523	1.5728	6
WOA-PSS	0.2002	0.1453	0.5716	1.0286	0.3078	1.7495	6

The results of fitness profiles, number of iteration N_j, minimum damping ratio ζ_{min} and maximum damping factor σ_{max} using C-PSS, EP-PSS, PSO-PSS and WOA-PSS for Case 1 are tabulated in Table 4. From the results, WOA-PSS optimized the highest value of J followed by PSO-PSS, EP-PSS and C-PSS. Results also show that the value of ζ_{min} and σ_{max} for WOA approach is higher than the other three techniques. From Table 4, both WOA and PSO were terminated in 6 iterations, while the EP was stopped at iteration 15. This shows that WOA and PSO give shorter computation time compared to EP. Overall, the proposed technique gives the best improvement in damping capability in the smallest number of iteration.

The response of speed deviation for Case 2 is shown in Figure 4(a). Here also, the proposed WOA-PSS system shows better damping and lower oscillation compared to other four techniques. The regions of eigenvalues location in complex s-plane for Case 2 as shown in Figure 4(b) indicate that WOA approach is more capable to improve the stability of the system by pushing the eigenvalues location far further to the left-hand side of the complex s-plane and closer to the real, σ axis. Table 5 tabulates the results for comparative studies using C-PSS, EP-PSS, PSO-PSS and WOA-PSS for Case 2. Results obtained shows that proposed technique achieve higher fitness compared to C-PSS, EP-PSS and PSO-PSS, as well as smaller number of iteration compared to EP-PSS and PSO-PSS.



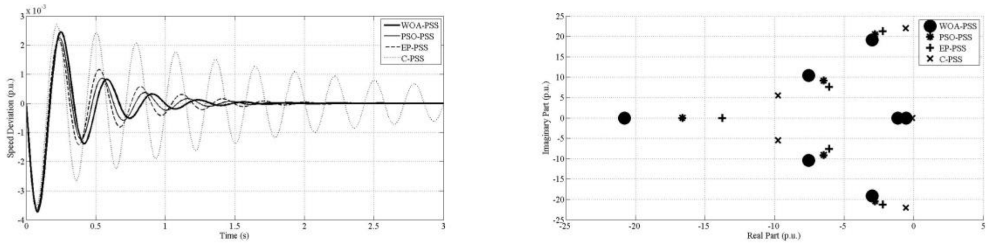
(a) Speed response (b) Complex s-plane

Figure 4. Speed response and complex s-plane for Case 2

Table 5. Comparison of C-PSS, EP-PSS, PSO-PSS and WA-PSS System for Case 2

Type	T_W	T_1	T_3	J	ξ_{min}	σ_{max}	N_i
C-PSS	10	10	10	0.0623	0.0547	0.0700	-
EP-PSS	0.2791	10.2263	11.2894	0.0964	0.1042	0.0886	7
PSO-PSS	0.1191	10.1194	10.2565	0.1380	0.1785	0.0975	4
WOA-PSS	0.0624	8.2263	19.2894	0.2160	0.3303	0.1018	3

The result of Case 3 is shown in Figure 5 and tabulated in Table 6. Almost similar results are experienced for Case 3 compared to the other two earlier cases. It was also discovered that WOA-PSS shows the best performance in terms of stability for SMIB system compared to EP-PSS, PSO-PSS and C-PSS.



(a) Speed response (b) Complex s-plane

Figure 5. Speed response and complex s-plane for Case 3

Table 6. Comparison of C-PSS, EP-PSS, PSO-PSS and WOA-PSS System for Case 3

Type	T_W	T_1	T_3	J	ξ_{min}	σ_{max}	N_i
C-PSS	10	10	10	0.0756	0.0256	0.1000	-
EP-PSS	0.1033	0.9421	2.3087	0.3199	0.1033	0.4331	12
PSO-PSS	0.069	0.8612	2.1217	0.3702	0.1345	0.4713	5
WOA-PSS	0.0472	0.8802	1.8139	0.4293	0.1537	0.5513	5

4. Conclusion

This paper proposed a new optimization approach for tuning PSS with LL controller. Three methods based on EP, PSO and WOA computation intelligence methods for optimizing T_W, T_1 and T_3 have been developed. Results obtained from the study indicated that WOA outperformed PSO and EP in terms of giving better values of T_W, T_1 and T_3 which are responsible for stability point determination. The performances are validated with respect to speed deviation response as well as eigenvalues, minimum damping ratio ζ_{min} and maximum damping factor σ_{max}.

Acknowledgement

The authors would like to acknowledge The Institute of Research Management and Innovation (IRMI) UiTM, Shah Alam, Selangor, Malaysia for the financial support of this research. This research is supported by LESTARI Grant Scheme with project code: 600-Dana/5/3/LESTARI (0117/2016).

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