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Intelligent swarm-based optimization technique for oscillatory stability assessment in power system

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ABSTRACT

This paper discussed the prediction of oscillatory stability condition of the power system using a particle swarm optimization (PSO) technique. Indicators namely synchronizing (Ks) and damping (Kd) torque coefficients is appointed to justify the angle stability condition in a multi-machine system. PSO is proposed and implemented to accelerate the determination of angle stability. The proposed algorithm has been confirmed to be more accurate with lower computation time compared with evolutionary programming (EP) technique. This result also supported with other indicators such as eigenvalues determination, damping ratio and least squares method. As a result, proposed technique is achievable to determine the oscillatory stability problems.

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1. INTRODUCTION

With the increase of energy consumption in this age, a study on the stability of the power system becomes a necessity, especially the oscillatory stability analysis of power systems. This analysis is used to predict electromagnetic swing at low frequencies as a result of undisturbed rotor swing. References [1-10] pointed out that the stability of the oscillation in the power system is an important issue. As the power system operation changes over time, the stability of the small signal in this power system should be tracked online. Selected stability indicators are calculated from the data provided over time to track the system. These indicators are updated until a constant value is obtained. In this study, damping torque coefficient K_d and synchronizing torque coefficient K_s are used as stability indicators. Both K_s and K_d values must be positive so that the system can be classified as stable [8-10].

The least squares (LS) method is a technique commonly used to find the K_s and K_d values, as reported in [8-10]. However, data update requirements are a major weakness of the LS method. In addition, this technique also requires a long computation time. Due to these problems, the LS method requires monitoring throughout the duration of the swing. Computational intelligence methods are generally used to solve problems in power system stability. Optimisation methods include artificial neural network (ANN) [11-13], Genetic Algorithm (GA) [14-16], evolutionary programming (EP) [17-21] and Artificial Immune Systems (AIS) [22-24]. ANN is the processing systems that inspired by biological neural networks that make up the animal brains. Such systems can learn to perform tasks by considering the examples given. On the other hand, GA is a search technique in which the application is based on the combination of natural selection and genetic mechanisms. Major characteristic in GA is the crossover and mutation operations which able it to produces high quality solution. The set back of GA is it took too long time to converge. Meanwhile, EP and AIS are heuristic population-based search methods that used random variation, mutation and selection. Something that distinguishes them is AIS also highlighted a process called cloning. This paper discussed a new heuristic approach named Particle Swarm Optimization (PSO) technique [25-29]. PSO is influenced by the behaviours of schools of fish and flocks of birds. It shows performance beyond EP, AIS and GA methods in searching the optimal solution with faster computation time.

This paper proposes an efficient technique for estimating synchronizing and damping torque coefficients in solving oscillatory stability problems. Using this technique, K_s and K_d values are estimated based on information by three generator responses, namely, the changes in rotor speed ($\Delta\omega(t)$), the changes in rotor angle ($\Delta\delta(t)$) and the changes in electromechanical torque ($\Delta T_e(t)$). The goal is to minimize the error of the estimated coefficients. The IEEE 30-Bus system has been chosen to test the online estimation technique for K_s and K_d. This paper discussed the oscillatory stability prediction in a multi-machine system using PSO. A mathematical model for IEEE 30-Bus system for the angle stability assessment is developed. PSO is chosen to optimize the objective function, with J as well as K_s and K_d as the control variables. Once the J value has been maximized, K_s and K_d are analyzed, which verify the stability condition of the system. The performance of PSO is then compared with EP and LS. Results obtained from the experiment are then verified with the minimum damping ratio (ξ_{min}) [30-32] and eigenvalues (λ).

2. IMPLEMENTATION OF ANGLE STABILITY ANALYSIS

The IEEE 30-Bus system model is selected to demonstrate the potential of the proposed technique in angle stability assessment for a multi-machine system. Six generators, namely, Generators 1, 2, 5, 8, 11 and 13 are connected to the buses named Buses 1, 2, 5, 8, 11 and 13, respectively. Reference [9] shows the parameters of the system.

2.1. Philips-heffron model for multi-machine system

The proposed Phillips-Heffron model for the multi machine system is developed and shown in Figure 1. The model is developed on the basis of the single machine of the Philips–Heffron model [10]. K_d is the damping torque coefficient, H is the inertia constant, T_A and K_A are the time constant and circuit constant of the exciter, respectively. ω_0 is equal to $2\pi f_0$. K_1~K_6 and T_3 are constants that consist of the function related to the operating real and reactive loading, impedance, electrical torque, and the excitation levels in the generator.

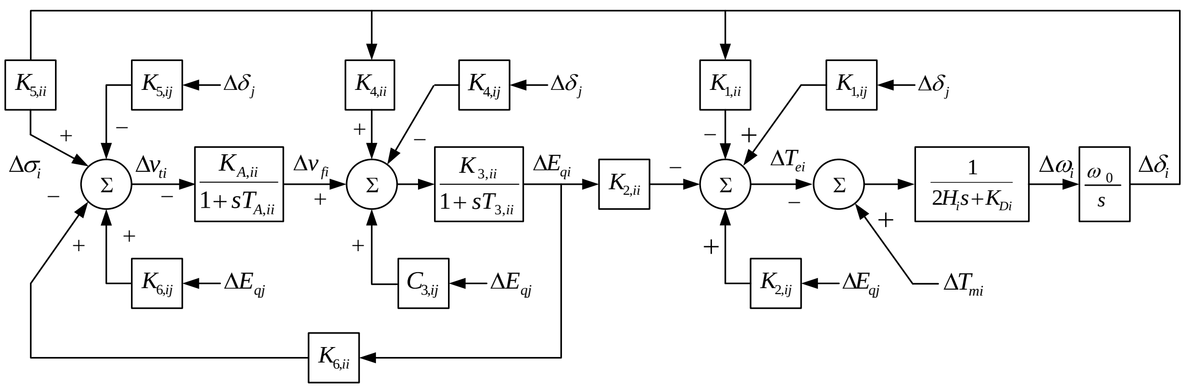


Figure 1. Phillips-heffron model for multi-machine system

2.2. Mathematical modelling of philips-heffron model

Mathematical modelling can be derived for the proposed Phillips–Heffron model for the multi machine system shown in Figure 1 and is presented in the following mathematical equations:

$$\Delta\omega_i/\Delta t = (\Delta T_{mi} - \Delta T_{ei} - K_{Di}\Delta\omega_i)/2H_i\,, i = 1, \dots, m \quad (1)$$

$$\Delta\delta_i/\Delta t = \omega_0\Delta\omega_i, i = 1, \dots, m \tag{2}$$

$$\Delta E_{qi}/\Delta t = \begin{pmatrix} K_{4,ii}\Delta\delta_i - \sum_{j\neq i} K_{4,ij}\Delta\delta_j - C_{3,ii}\Delta E'_{qi} \\ + \sum_{j\neq i} C_{3,ij}\Delta E'_{qj} + \Delta v_{fi} \end{pmatrix} / \Delta T'_{d0i}\,,\ i = 1, \dots, m, \quad j = 1, \dots, m, \quad i \neq j \tag{3}$$

$$\Delta v_{fi}/\Delta t = \begin{pmatrix} -K_{5,ii}\Delta\delta_i + \sum_{j\neq i} K_{5,ij}\Delta\delta_j \\ -K_{6,ii}\Delta E'_{qi} + \sum_{j\neq i} K_{6,ij}\Delta E'_{qj} \end{pmatrix} / T_{Ai} - \Delta v_{fi}/\Delta T_{Ai}\,,\ i = 1, \dots, m, \quad j = 1, \dots, m, \quad i \neq j \tag{4}$$

$$\Delta T_{ei} = \begin{pmatrix} K_{1,ii}\Delta\delta_i - \sum_{j\neq i} K_{1,ij}\Delta\delta_j \\ +K_{1,ii}\Delta E'_{qi} - \sum_{j\neq i} K_{2,ij}\Delta E'_{qj} \end{pmatrix},\ i = 1, \dots, m, \quad j = 1, \dots, m, \quad i \neq j \tag{5}$$

Reference [3] showed the details on (1-5). Can be rewritten into matrix form as follows:

$$\dot{X}_i = A_i \cdot X_i + B_i \cdot U_i, i = 1, \dots, m \tag{6}$$

$$X_i = [\Delta\omega_i \quad \Delta\delta_i \quad \Delta E_{qi} \quad \Delta v_{fi}]^T, i = 1, \dots, m \tag{7}$$

$$U_i = [\Delta T_{ei}], i = 1, \dots, m \tag{8}$$

U_i and X_i are the input and state signal vectors for i generators, respectively. A_i is the system parameters' function with i generators. B_i is the disturbance matrix.

2.3. Synchronizing and damping torque coefficients

The correlation between the change in estimated electromagnetic torque deviation ($\Delta T_{esi}(t)$) and the changes in rotor angle ($\Delta\delta_i(t)$) and rotor speed ($\Delta\omega_i(t)$) for the ith generator can be expressed as follows:

$$\Delta T_{esi}(t) = K_{si}\Delta\delta_i(t) + K_{di}\Delta\omega_i(t), i = 1, \dots, m \tag{9}$$

where K_{si} and K_{di} are K_s and K_d for the ith generator, respectively, and m is the number of generators. The justification of the stability of a linear system can be performed via the estimation of K_s and K_d. The positive values of K_s and K_d will validate the system as stable. If the system has positive K_S and negative K_d, then it is defined to be in the oscillatory instability condition. However, if K_s and K_d indicate negative and positive values, respectively, then the system is considered to be in the non-oscillatory instability condition. In general, the system is unstable if either one of the torque coefficients is negative.

The stability evaluation of a linear system can be predicted with reference to the K_s and K_d values. A stable system is guaranteed if the K_s and K_d values are positive. If the linear system has positive K_s and negative K_d, then the system is defined to be in the oscillatory instability condition. The effect of the oscillatory instability condition can be detected from the increment of the amplitude oscillations of the rotor. Non-oscillatory instability occurs if K_s and K_d show negative and positive values, respectively. This condition can be verified from the steady increment of rotor angle responses. Detail illustration of stable, oscillatory unstable and non-oscillatory unstable conditions can be found in [1].

2.4. Eigenvalues and damping ratio

The scalar parameter of eigenvalues, λ can be derived as follows [1]:

$$(A - \lambda I)\varphi = 0 \tag{10}$$

Here, the n solutions of λ ($=\lambda_1, \lambda_2, \dots, \lambda_n$) are the eigenvalues of A. The i^{th} eigenvalue can be stated as follows:

$$\lambda_i = \sigma_i \pm j\omega_i \tag{11}$$

where σ_i and ω_i are the real and the imaginary part of the i^{th} eigenvalue, respectively. If all value of λ have negative real parts, the linear system is considered stable. The damping ratio (ξ_i) for the i^{th} eigenvalue is defined as the following:

$$\xi_i = -\sigma_i/\sqrt{\sigma_i^2 + \omega_i^2} \tag{12}$$

The linear system is certainly in stable condition if all damping ratio have positive value. For simplification purposes, only the minimum value of the damping ratio, (ξ_{min}) for the linear system is selected to verify the result [30-32].

2.5. LS method

LS technique is often used to obtain the minimum value for the sum of the square of the differences between $\Delta T_e(t)$ and $\Delta T_{es}(t)$. The error is defined as [8-10]:

$$E(t) = \Delta T_e(t) - \Delta T_{es}(t) \tag{13}$$

Here, $\Delta T_e(t)$ and $\Delta T_{es}(t)$ are the real and estimated electrical torque, respectively.

The period of t_{total} must be chosen to estimate the correct value for K_s and K_d. The different values of t_{total} will result in an inaccurate value for K_s and K_d. References [8] stated that the suitable value for t_{total} that makes K_s and K_d constant during the oscillation period is the value of the entire oscillation period. In matrix notation, the problem can be described as follows:

$$\Delta T_e(t) = \Delta T_{es}(t) + E(t) = Cx + E(t) \tag{14}$$

$$C = [\Delta\delta(t) \quad \Delta\omega(t)] \tag{15}$$

$$x = [K_s \quad K_d]^T \tag{16}$$

Here $\Delta T_e(t)$ and $\Delta T_{es}(t)$ are the real and estimated electrical torque, respectively. $E(t)$ is the differences (error) between $\Delta T_e(t)$ and $\Delta T_{es}(t)$. Detail calculations can be found in [10]. Although the calculated values are accurate, the application of the LS method requires a full oscillation period and takes a long time [8]. Therefore, a new indicator is necessary.

3. OPTIMIZATION TECHNIQUES

Nowadays, artificial intelligence technology (AI) has been widely used in solving power system problems. Evolutionary computation (EC) is one of the AI techniques that promotes logical representation approaches. EC is a group of global optimization algorithms that has metaheuristic optimization properties. Inspired by biological evolution, among the techniques covered in EC are EP, GA, AIS and PSO. EP and PSO are selected as optimization techniques in the present study.

3.1. PSO

The PSO algorithm is started with initialization, followed by the update of velocity and position, fitness calculation, the best position update and convergence test. Detailed explanations of PSO algorithm process are as followed.

3.1.1. Initialization

In the initialization process of PSO, the value of synchronizing and damping torque coefficient, K_s and K_d are generated randomly. In the PSO perspective, K_s and K_d are called particles and their values are called position (or x). For every position that is created, x_i, there is a velocity, v_i. In the initialization process, the velocity is also randomly created in the range [0, 1]. The random positions are then used to calculate the fitness, J. In this initialization process, the i^{th} fitness, J_i is set as individual best fitness $J_{i,p}$ for i^{th} particle. For the K_s and K_d estimation process, one constraint is identified: the calculated J must be larger than 0.5. Initialization process is repeated until total number of initial particles, n is achieved. From these N set of particles, the maximum fitness of all particles, J_{max} is set as the global best fitness, J_g. The position for every $J_{i,p}$, J_{max} and J_g is set respectively as the individual best position p_i, position with maximum fitness p_{max} and global best position p_g.

a. Velocity and position update

After set of particles are selected in initialization level, all n particles are through a process of updating the velocity and position, for every particle. The update process of v_i and x_i for the i^{th} particle at j^{th} iteration is in line with the following equations:

$$v_i(j) = \omega v_i(j-1) + c_1\{p_i(j-1) - x_i(j-1)\} + c_2\{g(j-1) - x_i(j-1)\} \quad (17)$$

$$x_i(j) = v_i(j) + x_i(j-1) \quad (18)$$

Here, c_1 and c_2 are acceleration coefficients and ω is the inertia weight.

b. Fitness calculation

Using the new value of v_i and x_i, the new fitness, J_i are calculated for every new n particles. After new fitness is calculated, new value of J_{max} and the minimum fitness of all particles, J_{min} are selected.

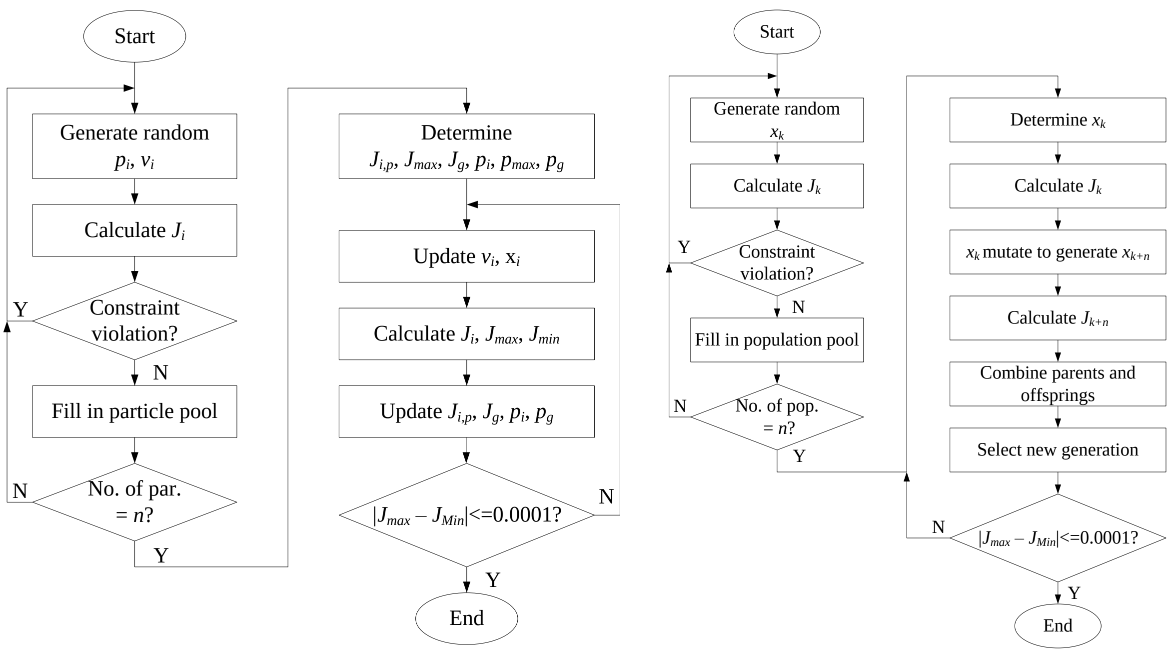
c. Best position update

With the new set of position, velocity and fitness for n particles, the update process of individual best position, p_i and the global best position, p_g will be performed if the following conditions are met:

– If J_i is bigger than $J_{i,p}$, select J_i as $J_{i,p}$, and select x_i as p_i. If J_i is smaller than or equal with $J_{i,p}$, the value of $J_{i,p}$ and p_i are not changed.
– If J_{max} is bigger than J_g, select J_{max} as J_g, and select p_{max} as p_g. Else, if J_{max} is smaller than or equal with J_g, the value of J_g and p_g are not changed.

d. Convergence test

Convergence test is attended to regulate the stopping criteria of the optimization process. The search process will be terminated if the process has reached the maximum iteration number or the difference between the value of J_{max} and J_{min} is very close to 0. The flow chart which represents the PSO algorithm is illustrated in Figure 2(a).



(a) PSO (b) EP

Figure 2. Algorithm flowchart

3.2. EP

The Evolutionary Programming (EP) is inspired by the theory of evolution based on natural selection. Metaphorically, the breeding of a species will produce offspring with some small variations due to mutations. With the competition between offspring and parents in finding the suitability of the environment, more suitable members will be chosen next generation. This new generation will reproduce, and this process repeats until the suitability between the species and the environment is reached. The overall process of EP algorithm is illustrated in Figure 2(b). Detailed explanations of EP algorithm process can be found in [10].

3.3. Objective functions

In the current study, the objective function formulated is based on the differences of the electromagnetic and estimated electromagnetic torques of the i^{th} generator, $\Delta T_{ei}(t)$ and $\Delta T_{esi}(t)$, respectively, as depicted in (21). This difference or error is estimated for the calculation of K_s and K_d for every generator in the system. The PSO optimization technique is used to minimize the error with K_s and K_d being the control variables [10].

$$J_i = inv\left(1 + abs\left(\left(\Delta T_{ei}(t) - \Delta T_{esi}(t)\right)/\Delta T_{ei}(t)\right)\right), i = 1, \dots, m \tag{19}$$

where m is the number of generators. Hence, the objective function can be defined as follows:

Maximize (J_i)

From the optimized J value, a decision can be made to identify the angle stability on the basis of the K_s and K_d values.

3.4. Algorithm for angle stability assessment

The calculation process of K_{si} and K_{di} for the i^{th} generator is conducted repeatedly to estimate successfully the maximum value of J_i. The following process is implemented:

a. Calculate $\Delta T_{esi}(t)$ using $\Delta_{\delta i}(t)$, $\Delta_{\omega i}(t)$, and the estimated torque coefficients using (9).
b. Evaluate J_i using (19).
c. If Ji is smaller than 1.00, then vary the values of Ksi and Kdi and repeat steps a and b with newly generated $\Delta_{\delta i}(t)$ and $\Delta_{\omega i}(t)$ sample data until J_i reaches 1.00 or all sample data are used.

Table 1 tabulates the parameters used in EP and PSO optimization process.

Table 1. Parameters of EP and PSO

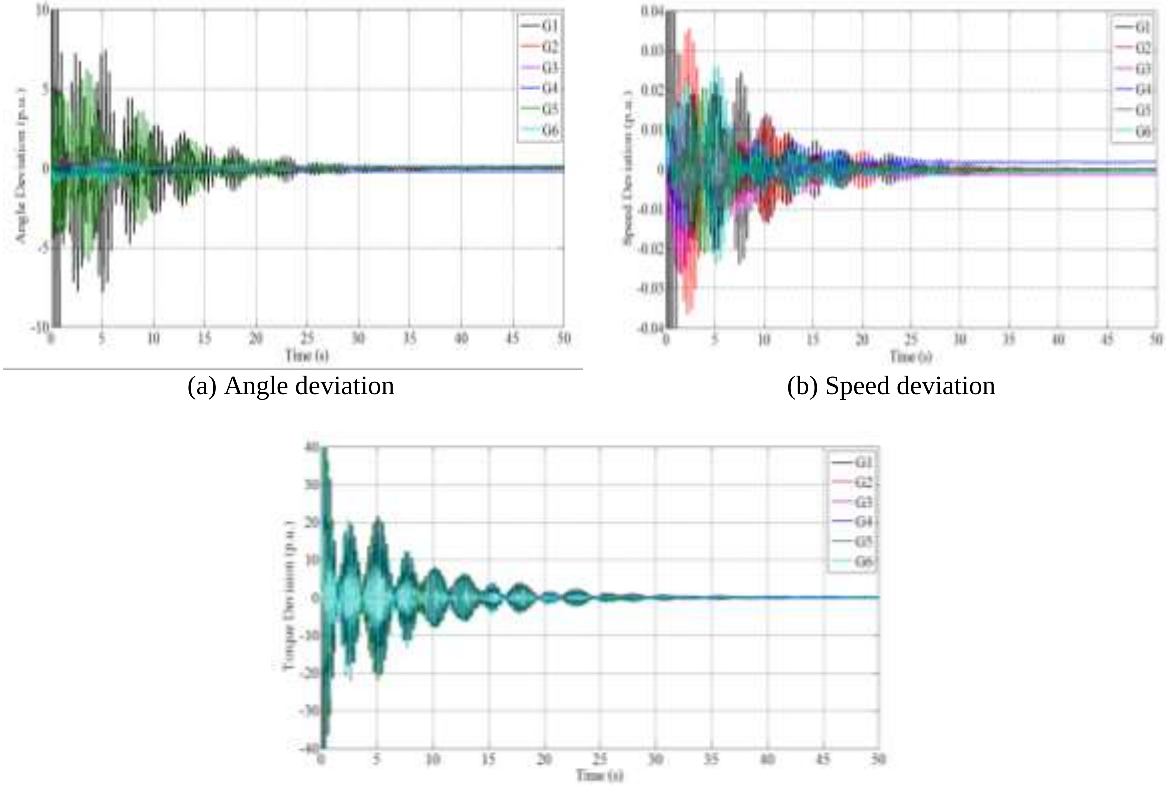
Techniques	EP	PSO
Parameters	$\beta = 0.09$	$c_1 = c_2 = 0.9$

4. RESULTS AND DISCUSSION

The achievement of the PSO technique in estimating K_s and K_d are conducted via the IEEE 30-bus system. Generator data for this system can be found in [7].Three samples of data of rotor angle $\Delta\delta(t)$, electrical torque $\Delta T_e(t)$ and rotor speed $\Delta\omega(t)$ for all six generators are produced in a MATLAB/Simulink environment. Two different values of reactive load at Bus 2 are used to simulate various stability cases. The values of the reactive load at Bus 2 are chosen in such a way that two scenarios can be emulated, namely, stable and critically unstable conditions as tabulated in Table 2. The three responses, namely angle, speed and torque deviations for Case 1 are shown in Figure 3(a), 3(b) and 3(c), respectively. In this case, the high damping rate for all responses justifies the system as in stable condition. Overall, all responses are fully damped 33 s after the simulation started.

Table 2. Two different loading conditions

Case	1 (stable condition)	2 (critically unstable condition)
Reactive load at Bus 2	35 Mvar	210 Mvar



(a) Angle deviation (b) Speed deviation

(c) Torque deviation

Figure 3. Responses for stable condition for all generators in case 1

Table 3 tabulates the comparison of K_s, K_d, J and number of iterations optimized for six different generators from EP, PSO and LS method for Case 1. All the three techniques manage to predict the stability conditions correctly indicated by the positive values of torque coefficients K_s and K_d for all the six generators. In this case, PSO method succeeds to calculate fitness value of 1.000 for all generators. On the other hand, EP calculated the highest fitness value of 0.8805 for generator G5. From the iteration perspective, PSO and EP are close to each other i.e. between 14~18 iterations. Table 4 shows the comparisons of fitness J and iteration result for Case 1. From eigenvalues λ perspective, all values are negative, meanwhile the minimum damping ratio ξ_{min} give positive value. This confirms that case 1 is a stable case.

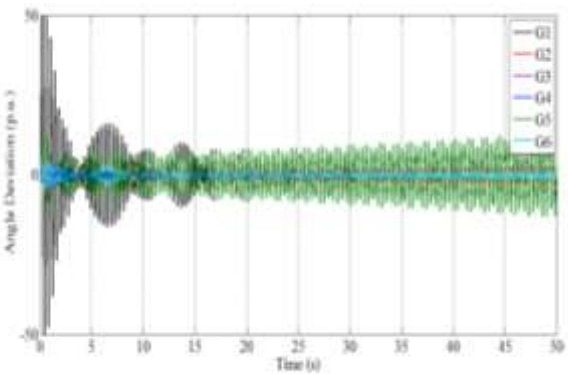
Table 3. Comparisons of EP, PSO and LS method for case 1

Gen.	Tech.	K_S	K_d	J	No. Iter.	Gen.	Tech.	K_S	K_d	J	No. Iter.
	EP	4.5152	6.7687	0.8204	17		EP	0.3305	0.6409	0.8077	15
G1	PSO	3.8295	7.7154	1.000	14	G4	PSO	0.6419	0.8375	1.0000	18
	LS	3.4122	7.1221	-	-		LS	0.5012	0.0819	-	-
	EP	0.0402	0.2196	0.8218	15		EP	1.7562	6.0567	0.8885	14
G2	PSO	0.1063	0.2285	1.0000	14	G5	PSO	1.4818	9.1044	1.0000	14
	LS	0.0903	0.0131	-	-		LS	1.1976	7.4533	-	-
	EP	9.1289	11.3642	0.8113	18		EP	4.3506	3.7928	0.8315	16
G3	PSO	7.6795	9.5289	1.0000	15	G6	PSO	3.7917	8.6296	1.0000	16
	LS	6.2812	10.3265	-	-		LS	4.0129	7.7373	-	-

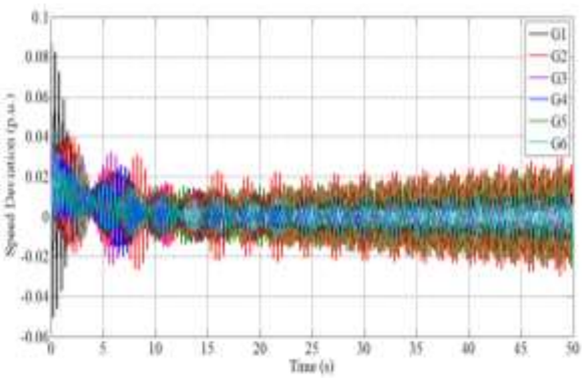
Table 4. The results of λ and ξ_{min} for case 1

ξ_{min}	λ
0.0071	-25.3277±j82.5561, -25.1949±j67.3925, -25.1835±j66.2373, -25.1689±j64.4594, -25.1727±j65.1107, -25.1770±j64.7891, -0.0321, -0.2579, -0.1240±j14.6853, -0.1257±j15.4743, -0.1142±j16.0849, -0.1424±j17.1449, -0.1409±j16.6304.

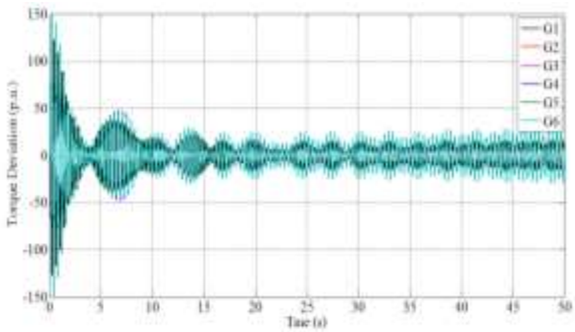
Case 2 is unstable case which supported by the oscillation increment of angle, speed and torque deviation for all six generators, shown in Figure 4(a), 4(b) and 4(c), respectively. Case 2 seems to damp in the first place, but after the simulation achieved in 15 seconds, the oscillation of the responses increasing dramatically until the simulation end. If analyzing the angle, speed or torque responses in short time i.e. 10-15 s, this case can be considered as a stable case. Unfortunately, if analyzing these three responses in 50 s and above, the oscillations seems increasing gradually and obviously the damping will not stop. Based on these results, Case 2.2B is considered as unstable case.



(a) Angle deviation



(b) Speed deviation



(c) Torque deviation

Figure 4. Responses for stable condition for all generators in case 2

The value of K_s, K_d, J and number of iterations for Case 2 are shown in Table 5. EP and PSO methods managed to calculate the instability conditions for Case 2 indicated by the negative results of K_d for all the six generators. On the other hand, LS failed to deliver correct results as this method calculated positive values for both K_s and K_d for generators G1 and G5. Based on this result, all the three optimization methods are highly recommended to assess the stability condition compare to LS technique. Results showed that PSO scored perfect 1.000 in fitness value at the end of the simulation process for all the six generators. EP never achieved value of 0.9 for this case. In terms of iteration number, PSO become the fastest method, followed by EP. From these results it can be said that PSO is the most capable technique in optimizing the highest quality of fitness in the calculation process with admissible computation time.

Table 5. Comparisons of EP, PSO and LS method for case 2

Gen.	Tech.	K_S	K_d	J	No. Iter.	Gen.	Tech.	K_S	K_d	J	No. Iter.
	EP	0.5182	-0.7726	0.7960	17		EP	-1.1044	-2.3948	0.8631	20
G1	PSO	0.6769	-0.5762	1.0000	15	G4	PSO	-0.9400	-1.7141	1.0000	15
	LS	0.0730	0.3147	-	-		LS	-0.9340	-1.0216	-	-
	EP	2.1324	-1.9547	0.8245	19		EP	2.1978	-0.5515	0.8583	20
G2	PSO	2.5784	-1.9975	0.9985	15	G5	PSO	2.5632	-0.7174	1.0000	16
	LS	2.6721	-1.8122	-	-		LS	2.6123	0.0022	-	-
	EP	-1.7429	-2.0883	0.7886	20		EP	-1.1044	-2.3947	0.8163	19
G3	PSO	-1.5087	-2.1320	0.9970	15	G6	PSO	-0.9400	-1.7141	1.0000	15
	LS	-1.0877	-1.9331	-	-		LS	-0.9218	-2.0166	-	-

Table 6. The results of λ and ξ_{min} for case 2

ξ_{min}	λ
-0.0013	-25.3894±j81.5538, -25.2323±j67.3359, -25.2296±j66.5607, -25.2493±j64.4474, -25.2044±j65.5412, -25.1783±j65.0325, -0.0014, -0.2568, 0.0184±j14.6126, -0.1184±j15.5915, -0.1250±j17.0943, -0.0364±j16.9197, -0.1278±j16.4524.

5. CONCLUSION

This study has discussed the effectiveness of PSO technique in the oscillatory stability prediction in a multi-machine system. In this study, the IEEE 30-Bus test system has been selected. Although both EP and PSO are capable to predict correctly the stability condition of all cases, PSO is more convincing compared to EP. Optimization via PSO produces higher accuracy for all cases compared with EP. From the iteration point of view, PSO and EP are almost the same.

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