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Stabilizing multimachine power systems with fuzzy logic using artificial bee colonies

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Abstract. Over the past few years, fuzzy logic systems have gained popularity due to their superiority over classical controllers when it comes to enhancing the transient stability of power systems. In this paper, a Fuzzy Logic Power System Stabilizer (FLPSS) is designed to damp local and inter-area oscillations following disturbances through the use of an Artificial Bee Colony Optimization Algorithm (ABC). The designed FLPSS is expected to significantly increase the robustness of power systems and ultimately improve the quality of power supply to end-users. This test system consists of two areas with four machines and eleven buses, with the purpose of evaluating the performance of the ABC-FLPSS under a variety of disturbances and loads. In order to optimize the scaling factors of FLPSSs, the Integral Squared Error (ISE) of rotor speed deviation is formulated as an objective function. Evaluation of the proposed controller involves simulating the test system under different conditions. These conditions range from small perturbations, such as changes in one of the system parameters, to large changes, such as removing a main transmission line, to determine its effectiveness. A comparison of ABC-FLPSS with FLPSS and Conventional Power System Stabilizer (CPSS) shows that the ABC-FLPSS controller is superior to FLPSS and CPSS.

Index Terms - Artificial Bee Colony (*ABC*), Fuzzy Logic Power System Stabilizer (FLPSS), Power System Transient Stability.

1. Introduction

In power system operation, the stability issue has been and remains a challenge. The major characteristics of modern electrical power systems are their size, their interconnectedness, and their complexity. There are several types of external disturbances that can cause low-frequency oscillations in these systems, including three-phase faults, load changes, generators tripping, and noise. It becomes increasingly difficult to maintain system stability. This oscillation should be compensated for by the synchronous generator excitation systems and the whole power system should be stabilized. There is a problem of dynamic oscillation in electrical power systems that are interconnected. In dynamic oscillations, there are two types of oscillation. The first type is local mode oscillations between generators in the same area, whereas the second type is inter-area mode oscillations between generators in different parts of the area, which is more complex. A power system's stability can be defined as its ability to maintain a stable equilibrium point under normal conditions and to converge to it under disturbed conditions. Because of its nonlinearity, it is very complex and difficult to manage or assess [1]. In order to provide better dynamic performance, synchronous machines require an excitation control system in order to ensure transient stability. In plant dynamic models, nonlinear differential equations are solved using time-domain analysis. A constant speed for the rotor machines is the objective of all stability analyses [2], [3].

The effects of PSSs on local and inter-area modes in multimachine power systems were simulated by Klein et al [4], [5]. It is concluded that the location of PSSs in the system network is a major factor in the design of PSSs controllers to get better results. Currently, there are different PSSs utilized in the industry such as proportional-integral-derivative PSSs (PID-PSS), and proportional-integral PSSs (PI-PSS) as well as the most used ones which are the conventional lead-lag PSSs (CPSS) [6]. To enhance the performance of PSSs, researchers proposed advanced techniques including robust control, adaptive control, and artificial and optimal optimization techniques [7], [8]. Recently, nonlinear controller design has gained popularity over the linear controllers which have limited operating points and these nonlinear controllers can maintain the stable dynamic performance of power systems over a wide range of operating regions [8], [9].

Fuzzy Logic Control is proven to be one of the most applicable approaches for nonlinear and time-varying systems because of its ability to handle uncertainties existing in the system model in addition to its robustness and short computational time. PSS based on fuzzy logic performs differently depending on the system's operating conditions. Therefore, Fuzzy Logic PSS parameters should be tuned according to the changing operating conditions of power systems to make it adaptable [10]-[14].

Fuzzy logic control is a rule-based control which means that it doesn't rely on the system's mathematical model. Hence, the most crucial step for designing an efficient Fuzzy Controller is considered the selection of optimal rules. For this purpose, the Genetic Algorithm in and ABC in [15] are used to generate fuzzy rules automatically. The automatic selection of fuzzy rules resulted in reducing the efforts of designing reliable fuzzy controllers and tackling the power system parametric uncertainties. Furthermore, these automated techniques increased the fuzzy controller's robustness and flexibility for various operating conditions.

In order to inject fuzzy input-output variables into the fuzzy controller, the variables have to be normalized first. Normalization factors (Scaling Factors) play an important role in improving fuzzy controller performance and should be carefully chosen. For this purpose, [16]-[18] use the Cuckoo Search algorithm. In [19], bat is used, and it performs better than Particle Swarm Optimization (PSO) in [20], and the Harmony Search Algorithm (HSA) in [22]. In this paper, the Artificial Bee Colony algorithm (ABC) has been used to optimize scaling factors of FLPSSs for two-area four-machine eleven-bus power systems. The performance of the proposed ABC-FPSS is to be compared to the FLPSS and the CPSS.

In 2005, Karaboga [23]invented the ABC technique, which is now used to solve many complex optimization problems. In this simulation, honeybee swarms are simulated as they forage. In addition to the common control parameters of population-based optimization algorithms such as population size and maximum number of iterations, ABC has a simple structure, ease of implementation, and only one control parameter called a limit (L).

The rest of the article is organized as follows. The problem of transient stability is introduced in Section I as a major issue in the control of multi-machine power systems Additionally, this section summarizes related literature work that has been done to address this issue. In Section II, the system methodology of the work is presented by describing the test model of the multi-machine power system. In addition, the fuzzy logic PSS controller is described. This is an optimization technique. An application of the proposed controller to an MMPS with various disturbances and the simulation results are carried out and discussed in Section III to investigate its performance. Finally, the conclusion is summarized in Section IV.

2. System Methodology

A. Test Power System

A dynamic model of the test power system used in this article represents two sets of generators in two separate areas. It generates 900MVA with a 20KV rating as shown in Fig. 1. There are two weak tie lines connecting the two areas. The active power from Area 1 is transferred to Area 2 in the form of 413MW. A total of about 700MW generators' loads, 967MW Area 1 loads, and 1767MW Area 2 loads are considered. More information about this power system such as the generator's parameters and transmission lines can be found in [24].

Generators are equipped with excitation systems. As the generator's speed deviation varies, its electric torque is induced by the PSS contained in its excitation system. As a result of parameter changes or fault disturbances, PSS provides an additional damping voltage to the Automatic Voltage Regulator (AVR) to compensate for the negative damping caused by a disturbed system.

CPSSs can be equipped with a wide variety of inputs, including the generator shaft speed deviation, the change in electrical power, and even the terminal bus frequency. Speed deviations are used as inputs to CPSS in this study. Voltage signals are produced only when a rotor oscillates or when the system oscillates.

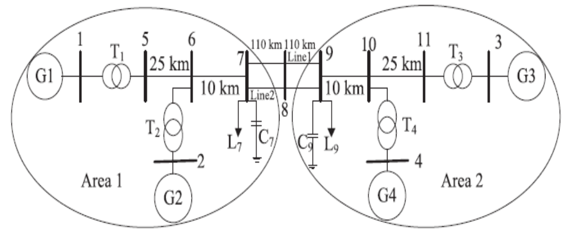

Fig. 1. Two-area, four-machine, eleven-bus test power system

The Structure of CPSS is shown in Fig. 2. The first block is a PSS gain (K_{pss}) which is responsible for providing the required positive damping, followed by a filter or washout block to reject low frequencies (0.8-2.0Hz) with time constant (T_w), after that two lead-lag phase compensator blocks were implemented with time constants T_1, T_2, T_3, T_4 in order to compensate for the phase lag between the input of the exciter and the electrical torque of the generator, and finally a voltage limiter block is installed in order to maintain constraints and prevent overexcitation [19]. The parameters used in this work are K_{pss}=20, T_w=10s, T_1=0.05s, T_2=0.02s, T_3=3s, T_4=5.4s, and $-0.15 \leq V_{pss} \leq 0.15$ [16]. Conventional PSS (CPSS) transfer function is as follows:

$$V_{pss}(s) = K_{pss} \times \frac{sT_w}{1+sT_w} \times \frac{1+sT_1}{1+sT_2} \times \frac{1+sT_3}{1+sT_4} \qquad (1)$$

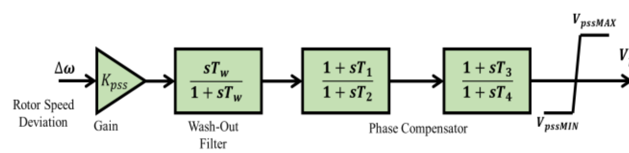

Fig. 2. Conventional Power System Stabilizer Structure

B. Fuzzy Logic based Power System Stabilizer

The PSS parameters are calculated by linearizing the system model around a specified operating point. Nevertheless, in practical nonlinear systems, this can lead to a degradation in controller performance due to continuous changes in system parameters [14]. Therefore, linear control theory has limitations in the design and analysis process. The fuzzy control theory, on the other hand, is a rule-based theory of control. A nonlinear environment of such constant change makes fuzzy logic control more effective in stabilizing excitation systems. Fuzzy Logic controller doesn't depend on the system mathematical model, although, the details of processing the inputs and generating the outputs should be clear [25]. The control action of the fuzzy logic control is performing in three main steps: fuzzification, Fuzzy Inference Rules and finally defuzzification.

1) Fuzzification

Two steps are involved in the fuzzing process. The first step is to measure and scale the input variables (speed, power and acceleration). The second step is to transform the measured crisp values into the corresponding fuzzy variables (linguistic variables) using membership functions. In order to generate fuzzy values for each system input variable, a membership function must be defined.

The two system input variables for the proposed controller are selected as the generator speed deviation and active power deviation whereas the system output variable is selected as an additional voltage signal which is required to stabilize the generator excitation system. In order to generate fuzzy rules for power system problems, a set of seven linguistic values are assigned to each system variable (input or output), ranging from Negative Big (NB) to Positive Big (PB). Fig. 3. illustrates the seven linguistic variables: Negative Big (NB), Negative Medium (NM), Negative Small (NS), Zero (Z), Positive Small (PS), Positive Medium (PM), and Positive Big (PB).

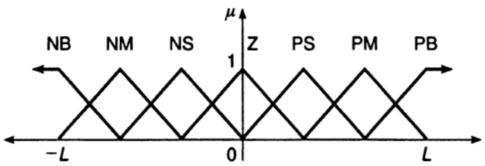

Fig. 3. Triangular Membership Function

Members can be shaped in many ways, but the most common ones are triangular, trapezoidal, and bell. A diagram of the triangular membership function can be found in Fig. 3 which is used for the proposed controller. In practice, membership functions are normalized in the interval $[-L, L]$, which is symmetric around zero. As a result, fuzzy variables are expressed in terms of controller parameters. As a result, we can define these parameters as follows:

$$K_i = \frac{2L}{X_{range_i}} \tag{2}$$

where X_{range_i} defines the control variable X_i full range that is:

$$X_{range_i} = X_{max_i} - X_{min_i} \tag{3}$$

and the maximum and minimum values of the control variable X_i are X_{max_i}, X_{min_i}. A FLC parameter is a set of input and output gains K_i. It is necessary to have prior knowledge of the controlled system in order to select these parameters more effectively.

2) Fuzzy Inference Rules

Allocating each input fuzzy values to their corresponding output values is done using a rule base. The rules are generated based on a common concept which states that: the output should be stabilized around a set point, according to this assumption a large, small or even zero control action is needed to satisfy it.

The proposed controller is Considered two input fuzzy variables and one output fuzzy variable, each quantized to seven fuzzy sets as shown in Table 1 Every entity in the matrix represents a rule. A design engineer, a simulation, or an expert operator can all contribute knowledge to generating fuzzy rules. [19].

3) Defuzzification

The maximum product and the minimum maximum methods can be used to determine the output based on the membership function. A special rule is applied to the membership function to obtain the output. The proposed fuzzy controller calculates the output membership function for each rule using the minimum and maximum methods. The generator excitation system is used a real (nonfuzzy) signals. Hence, the defuzzification process is necessary to get the actual values back again from their fuzzy. In the proposed controller, the centroid defuzzification method is used for this purpose.

Table 1. Fuzzy rules of the proposed fuzzy Logic Controller

$\Delta\omega$ / Δp	NB	NM	NS	Z	PS	PM	PB
NB	NB	NB	NB	NB	NM	NS	Z
NM	NB	NB	NM	NM	NS	Z	PS
NS	NB	NM	NM	NS	Z	PS	PM
Z	NM	NM	NS	Z	PS	PM	PM
PS	NM	NS	Z	PS	PM	PM	PB
PM	NS	Z	PS	PM	PM	PB	PB
PB	Z	PS	PM	PB	PB	PB	PB

C. Artificial Bee Colony Optimization Algorithm

Aside from these features, the ABC algorithm has many advantages such as flexible structure, short computational time, robustness, and ease of implementation and tuning. These advantages make it suitable for the implementation of complex power systems in the real world.

Forage selection involves three essential components as Follows:

- Food Sources: they are one possible solution to the optimized problem.
- Employed bees: Their current food source is associated with them.
- Unemployed bees: They are waiting for the employed bees to provide them with information. Among the unemployed bees, there are scouts looking for new food sources around the nest, and onlookers, waiting in the nest and making decisions based on the information provided by employed bees.

The more details steps ABC technique are described below:

1) Initial Population

Initially, ABC algorithms generate SN random D-dimensional vectors, where SN represents the number of food sources. Among the population, the primary food source is $X_i = (x_{i,1}, x_{i,2}, \ldots, x_{i,n})$. Thus, the following are the initial food sources:

$$x_{i,j} = x_j^{min} + rand(0,1)\left(x_j^{max} - x_j^{min}\right) \tag{4}$$
$$i = 1,2,3,\ldots,n \qquad j = 1,2,3,\ldots,D$$

Where D is the number of optimized parameters. x_j^{min} and x_j^{max} are the lower and upper bounds of j respectively. After generating the initial population, iterative search process is applied on it by three bees types the employed bees, the onlooker bees and the scout bees as will be described in the following sections:

2) Employed Bee Phase

New candidate solution V_i is generated about its current position by each employed bee X_i. The position of the new solution is defined as:

$$v_{i,j} = x_{i,j} + \emptyset_{i,j}(x_{i,j} - x_{k,j}) \quad (5)$$

where $k = 1,2,3, \ldots, SN$ and $j = 1,2,3, \ldots, D$ are random indexes, k must be different from i. $\emptyset_{i,j}$ is a random number in the period [−1, 1].

If a parameter value (5) exceeds its limits, the parameter will be fixed to its limit value. The fitness value of candidate solution V_i is calculated. If V_i's fitness value is equal to or greater than X_i's fitness value, X_i will be replaced by V_i., otherwise X_i will be retained.

3) Onlooker Bee Probability calculation

A food source is selected by every onlooker bee based on a food source probability calculated by the following equation after the employed bees have finished their search:

$$P_i = \frac{fitness_i}{\sum_{n=1}^{SN} fitness_i} \quad (6)$$

The more fit a food source is, the greater the chance it will be chosen by onlooker bees.

4) Unemployed Bee Phase

Onlooker bee produces a modification on X_i, after its selection, using Eq. (5). If the fitness of this modified solution is equal or better than of the previous one, X_i will be replaced by the modified solution. A food source X_i is replaced by a new food source discovered by the scout bee after a predetermined number of generations. As a result of the following equation, the scout bee generates a new food source:

$$x_{i,j} = x_j^{max} + rand(0,1)(x_j^{max} - x_j^{min}) \quad (7)$$

D. Objective Function

An ABC optimization algorithm is used in the proposed work to determine the optimum scaling factors for the Fuzzy Logic PSS controller.

FLPSS input-output variables are speed deviation (($\Delta\omega$) and power acceleration ((Δp) for inputs, and correction voltage change ((Δu) for outputs, with associated scaling factors K_ω, K_p and K_u. An objective function for optimizing fuzzy logic scaling factors is the integral of squared error (ISE) of generator speed deviation. The ISE based cost function for the test system is represented by Eq. (8). The parameter bounds are as showing in equation (9).

$$J = \sum_{i=1}^{4} \int_0^{T_{sim}} |\Delta\omega_i(t)|^2 . dt \quad (8)$$

$$\begin{gathered} K_{\omega i}{}^{min} \le K_{\omega i} \le K_{\omega i}{}^{max} \\ K_{pi}{}^{min} \le K_{pi} \le K_{pi}{}^{max} \\ K_{ui}{}^{min} \le K_{ui} \le K_{ui}{}^{max} \end{gathered} \quad (9)$$

In this case, i is the ith generator and T_{sim} is the simulation time. As shown in Fig. 4, FLPSS uses a scaling factor scheme. An optimal set of input-output fuzzy logic scaling factors is obtained using the ABC algorithm to minimize the speed deviation.

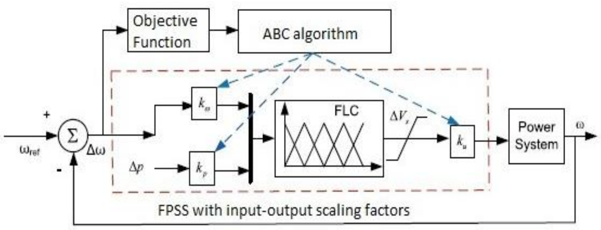

Fig. 4. ABC algorithm for tuning FLPSS input-output scaling factors

3. Simulation Results and Discussion

Test power systems with two-area four-machine eleven-bus multimachine power systems are used to analyze the performance of the proposed controller. Two separate areas are connected by weak tie-lines. Each area consists of two synchronous machines connected to an infinite bus. Generator two serves as a reference for the system. The behavior of this system in practical operation resembles that of typical power systems despite its small size (See Fig. 1).

The test power system is equipped with FLPSS as designed in section 2.2 along with input-output scaling factors optimized by ABC algorithm as designed in section 2.3, the tuning scheme is shown in Fig. 4. A trial-and-error method is used to select the initial parameters. As a result of several attempts, the initial parameters were found to be: population size (number of food sources) and employed bees equal to five, which is the number of onlooker bees, and the maximum number of iterations is 50, which ends the optimization search. All input-output FLPSS scaling factors have the same parameter bounds as $1 \le K_{\omega i}$, K_{pi}, $K_{ui} \le 3$. Fig. 5 shows how the ABC optimization algorithm converges as the number of iterations increases. Table 2 lists the optimal set of input-output scaling factors using the ABC algorithm.

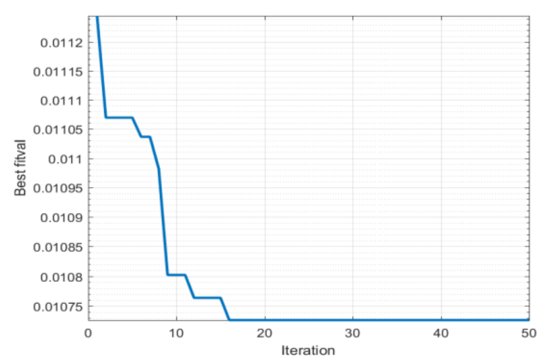

Fig. 5. Objective Function Convergence of ABC Optimization Algorithm

The simulation is done under various disturbance imposed to the system including:

- Three-phase symmetrical fault at the terminal of generator 1.
- Three-phase symmetrical fault at the middle of transmission Line1.

Table 2: The optimal set of input-output FLPSS scaling factors using the ABC algorithm for a 2-area 4-machine 11-bus test power system

Simulated in steady state from (0-1s) in all scenarios above, then a disturbance is applied at t=1s for (0.2s). Based on the disturbances given above, the proposed controller was compared to a conventional power system stabilizer as proposed in [24]. The results are summarized as follow:

Parameter \ Generator	G1	G2	G3	G4
$K_{\omega i}$	1	1.0170	1.0495	2.4589
K_{pi}	1.6657	1.3569	3	1.3075
K_{ui}	1.1488	1.0150	1.7374	1.4932

A. Three-phase fault at the terminal of generator 1

An application of a three-phase fault at the terminal of generator 1 for 12 cycles is considered the most critical scenario. As shown in Fig. 6., the terminal voltage of generator 1 is reduced to zero during the fault condition and returns to its pre-fault condition after removal of the fault. Generator 3's terminal voltage is also disturbed and stabilized to pre-fault levels.

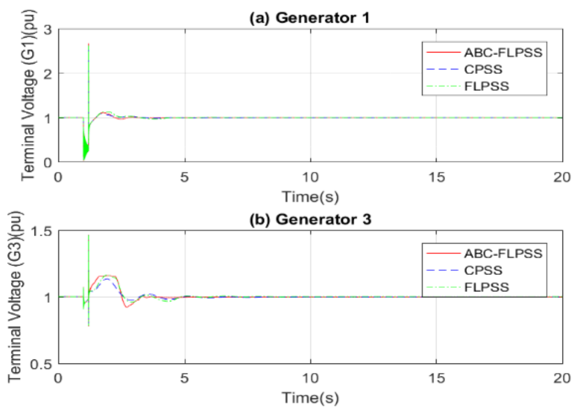

Fig. 6 Generator #1 terminal voltages with a three-phase fault

The corresponding speed deviation and rotor angle of generator 1 and generator 3 are represented in Fig. 7 and Fig. 8 respectively. As can be obviously seen from Fig. 7, All controllers achieve zero speed deviation during the post-fault condition. The proposed ABC-FLPSS, however, outperforms the other controllers during a fault condition, which proves its superiority. Such superiority can also be seen from the rotor angle responses of generator 1 and generator 3 as shown in Fig. 8.

B. Three Phase Fault at the middle of Transmission Line 1

During this scenario, a three-phase to ground symmetrical fault occurs on the middle of transmission line 1 between buses 7 and 8, which is one of the most important transmission lines responsible for the transfer of power between areas 1 and 2.Fig. 9 shows the terminal voltage responses of generator 1 and generator 3 with the CPSS, the FLPSS and the proposed ABC-FLPSS where the proposed ABC-FLPSS settles down to pre-fault condition earlier than the other controllers. Speed and rotor angle deviations of generator 1 and generator 3 are shown in Fig. 10 and Fig. 11, respectively. It is clearly shown that with ABC-FLPSS the convergence is much faster than CPSS and FLPSS.

4. Conclusion

In contrast to classical controllers that require precise mathematical modeling and measurements, fuzzy logic controllers can handle uncertainty in nonlinear dynamic systems. A fuzzy logic PSS with fuzzy logic input-output scaling factors was used in this paper for the purpose of enhancing the transient stability of multimachine power systems using the Artificial Bee Colony optimization technique. We compare the developed controller with conventional power system stabilizers through nonlinear time-domain simulations of generator rotor angles and speeds. According to simulation results, multi-machine power systems are more stable and robust when they are subjected to external disturbances when using ABC-FLPSS as opposed than CPSS. As a result of ABC-FLPSS, inter-area oscillations are dampened more effectively under small and large disturbances, despite changing operating conditions.

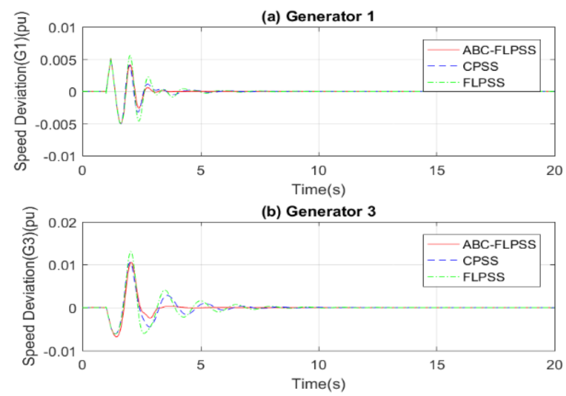

Fig. 7 Generator #1 speed deviations with three-phase faults.

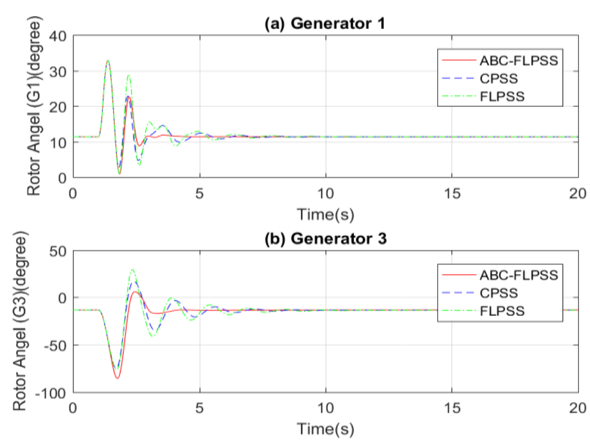

Fig. 8 Generator #1 rotor angles with three-phase fault

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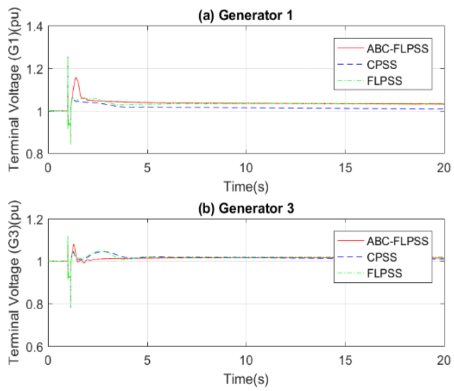

Fig. 9. Transmission line #1 terminal voltages with a three-phase fault

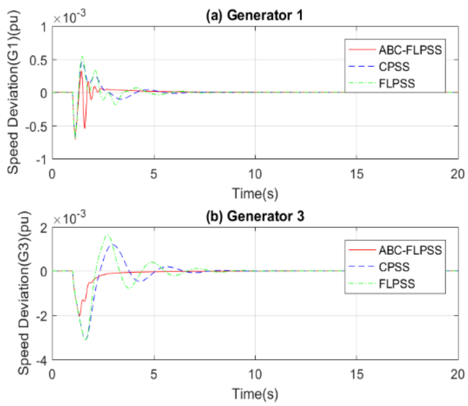

Fig. 10. Transmission Line #1 speed deviations with a three-phase fault

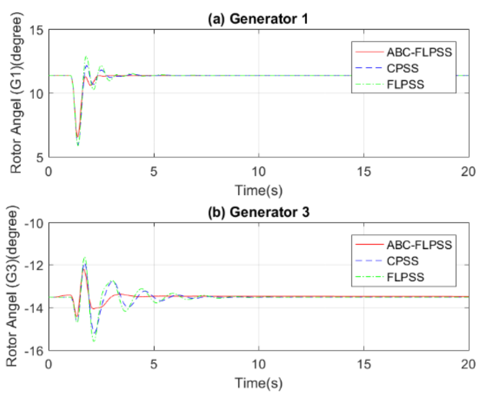

Fig. 11. Transmission Line 1 rotor angles with a three-phase fault

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