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Power System Stabilizer Based on Artificial Bee Colony Algorithms.

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Abstract. Transient stability of power systems is increasingly enhanced through the use of fuzzy logic systems compared with classical controllers. Fuzzy Logic Power System Stabilizers (FLPSS) are optimized in this paper using an Artificial Bee Colony Optimization Algorithm (ABC). ABC-FLPSS has been evaluated using two-area 4-machine and eleven-bus multimachine power systems. For optimizing fuzzy logic power system stabilizer scaling factors, an objective function is formulated as the Integral Squared Error of rotor speed deviation. Changes in parameter values as well as removal of transmission lines are evaluated. Compared to FLPSS and CPSS, ABC-FLPSS controller is superior in performance. ABC-FLPSS controllers are capable of maintaining system stability with fewer parameters. Additionally, it can reduce power loss and dampen oscillations. Furthermore, it can be easily integrated into existing power systems. The ABC-FLPSS controller showed improved transient stability compared to FLPSS and CPSS, even with the removal of one transmission line. This demonstrates its robustness and ability to maintain system stability under changing conditions. Adjusting the mechanical power input of Generator 3 resulted in enhanced stability when controlled by the ABC-FLPSS. This highlights its effectiveness in optimizing power system performance.

Key word. Transient Stability, Artificial Bee Colony Optimization Algorithm (ABC), Fuzzy Logic Power System Stabilizer (FLPSS)

1. Introduction

In power system operation, the stability problem has been and remains a challenge. Electricity systems of the modern era are large, interconnected, and complex systems. Low-frequency oscillations occur in these systems as a result of many factors, including three-phase faults, load changes, and generator trips. It is difficult to maintain system stability in these situations, and additional damping should be provided by the synchronous generator excitation system to compensate for these oscillations and stabilize the whole power system. In interconnected electrical power systems, dynamic oscillation is a critical problem. Dynamic oscillation is divided into two kinds. There are two types of oscillation between generators: local mode oscillation between the generators within the same area and inter-area mode oscillation between the generators within different areas.

The ability of a power system to maintain synchronized operation between its machines is an indication of its transient stability. An equilibrium point under normal conditions can also be maintained and convergent under disturbances. Due to its nonlinear nature, this problem is very challenging to evaluate and control [1]. For synchronous machines to perform dynamically and maintain transient stability, excitation control is required. For solving nonlinear differential equations in a dynamical model of a plant, the time-domain analysis is widely used. Rotor machines must be maintained at a constant speed in all stability analyses (PSSs). Generator excitation systems are traditionally controlled through power system stabilizers. Local modes are effectively dampened by PSSs. It is possible that PSSs won't provide enough damping voltage to damp out interarea modes in large interarea power systems. As a result, PSSs need to be replaced with more efficient alternatives. multi-machine power systems (MMPS) and Single Machine Infinite Bus power systems were significantly improved by DeMello and Concordia in 1969 [2].

In multimachine power systems, the references [3], [4] simulated the effects of PSSs on local and inter-area modes. In order to get better results, PSSs controllers should be designed based on the location of PSSs in the system network. In the industry, there are different PSSs, including proportional-integral-derivative PSSs (PID-PSSs), proportional-integral PSSs (PI-PSSs), as well as conventional lead-lag PSSs (CPSSs) [3], [4]. These techniques allow PSSs controllers to be tailored to the specific needs of the system. Additionally, these techniques can provide better dynamic performance and improved stability. A wide range of operating conditions were maintained by these nonlinear controllers [5]. According to some recent literature on power system stability, uncertain parameters have a strong influence on dynamic stability. Inertia constant, direct-axis time constant, and damping coefficient are some of the parameters that degrade power system stability. Controllers usually use nominal values for these parameters, unless they are difficult to measure or are slowly changing over time. Due to the saturation effect, the transient reactance of the generator may gradually vary regardless of the damping coefficient.

A number of nonlinear and time-varying systems can be controlled using Fuzzy Logic Control because of its ability to handle uncertainties, as well as its robustness and short computation time. In order for Fuzzy Logic PSS to be adaptable and get a better response, the parameters should be adjusted in accordance with the changing operating conditions of power systems [6]. In contrast to mathematical models, fuzzy logic control relies on rules instead of mathematical models of the system. For this reason, selecting optimal rules is considered essential when designing fuzzy controllers. In [7] and [8] fuzzy rules are generated automatically using the Genetic Algorithm and the ABC algorithm. As a result of the automatic selection of fuzzy rules, the effort necessary to design reliable fuzzy controllers was reduced, as well as to deal with the parametric uncertainties in power systems. In addition, these automated techniques increased the fuzzy controller's robustness and flexibility.

A fuzzy controller must be injected with normalized inputs and outputs. Scaling factors (normalization factors) must be carefully selected to improve fuzzy controller performance. According to [9], this is achieved using the Cuckoo Search algorithm. According to [10]-[13], bat algorithms outperformed particle swarm optimization and Harmony Search Algorithms (HSA). A proposed ABC Algorithm is used in this paper to optimize scaling factors for FLPSSs with two areas, four machines, and eleven buses. A comparison will be made between the ABC-FPSS and the FLPSS and CPSS. The ABC-FPSS was shown to be more effective than the FLP and CPSS in minimizing the cost of the overall system. Furthermore, the ABC-FPSS was able to reduce the complexity of the system compared to the other two algorithms.

Following is the rest of the article. Managing MMPS requires the control of transient stability, as described in Section 1. Furthermore, this section provides an overview of the literature related to this problem. As an optimization technique, we describe the fuzzy logic PSS controller with an artificial bee colony as an introduction to the methodology of the work presented in Section 2. The performance of the proposed controller is examined in Section 3 by using it on an MMPS with various disturbances. As a final section, Section 4 discusses and summarizes the conclusions and results.

2. Power System Testing Methodology

This paper employs two separate test power systems with 900MVA and 20kV generators each, as illustrated in Fig. 1. There are two areas that are exactly the same and they are connected by two weak tie lines. An active power transfer of 1413MW occurs between Areas 1 and 2. The generator loads amount to approximately 700MW, Area 1 loads amount to 967MW, and Area 2 loads amount to 1767MW. In [14], [15] The generator's parameters and transmission lines are available for this power system.

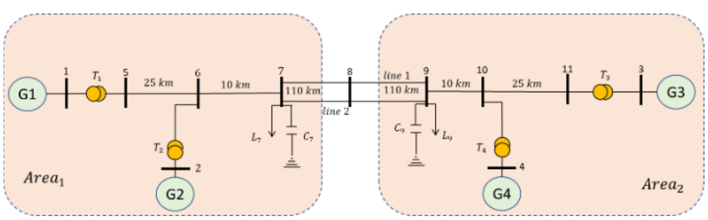

Fig. 1: Test power systems with two areas, four machines, and eleven buses.

Excitation systems are installed on each generator. According to Fig. 2, PSS induces an electric torque by causing the generator's excitation system to follow the rotor's speed deviation. AVR receives an additional stabilizing signal when the parameters are changed, or the fault occurs. This compensatory signal compensates for negative damping caused by the disturbance. There are multiple inputs that can be used by the CPSS, such as the speed deviation of the generator shaft, a change in the electrical power or acceleration power, or even the frequency of the terminal bus. An oscillating rotor is considered a driving force for CPSS, and speed deviation is used as an input, while a voltage signal is the output of any CPSS. The CPSS is designed to respond to changes in the input signal and adjust the output voltage accordingly. The CPSS can also detect any changes in the input signal and take appropriate action to maintain the desired output voltage.

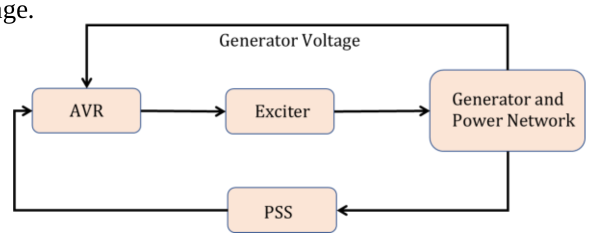

Fig. 2: Generator Excitation system with Power System Stabilizer

The Structure of CPSS is shown in Figure 2. The first block is a PSS gain (K_{pss}) which 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 existed with time constants T_1, T_2, T_3, T_4 to provide the appropriate phase lead characteristic to compensate for the phase lag between the exciter input and the generator electrical torque, finally a voltage limiter block is installed to sustain the constrains and avoid over-excitation [16]. The parameters used in this paper are K_{pss}=20, T_w=10s, T_1=0.05s, T_2=0.02s, T_3=3s, T_4=5.4s, and $-0.15 \le V_{pss} \le 0.15$ [15]. The transfer function of the Conventional PSS (CPSS) is given by:

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

3. Stabilizer Based on Fuzzy Logic

In linear control theory, PSS parameters can be calculated by linearizing the system model around a given operating point, but linear control theory has limitations when dealing with nonlinear systems [10]. Fig. 3 illustrates how fuzzy control theory is based on rules. CPSS is inefficient in a changing nonlinear environment, where fuzzy logic control provides a more efficient stabilizing signal. It doesn't depend on the system's mathematical model, but it should be clear how inputs and outputs are processed [17]. Fuzzy logic control involves three main steps: fuzzy inference rules, fuzzification, and defuzzification.

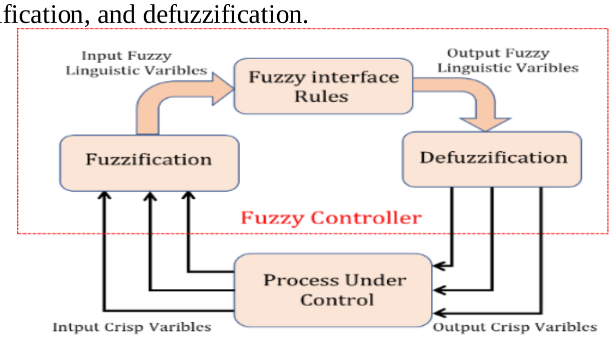

Fig. 3: Fuzzy Control concept

Fuzzification: the choice of membership functions can greatly affect fuzzy values. Different membership functions can lead to different degrees of fuzziness and impact the overall performance and behavior of the fuzzy system. It is imperative to carefully consider the shape and parameters of membership functions to accurately represent linguistic variables. This will capture the desired fuzziness.

A proposed controller is designed with two system input variables, generator speed deviation and active power deviation, and an additional voltage signal, which stabilizes the generator excitation system. Each system variable (input or output) is assigned seven linguistic values, ranging from Negative Big to Positive Big, which can be used to generate fuzzy rules for power system problems. Using linguistic variables in data analysis allows for a more flexible and nuanced representation of data. It enables us to capture and analyze the inherent ambiguity and uncertainty in human language, which is often missing in traditional numerical data analysis. By incorporating linguistic variables, we can better understand and interpret complex patterns and relationships within the data, leading to more accurate decision-making and insights.

Triangular, trapezoidal, and bell membership functions are the most common shapes of membership functions. In practice, membership functions are normalized around zero $[-L, L]$. Fuzzy variables are expressed in controller parameters. Parameters such as these can be defined as follows:

$$K_i = \frac{2L}{X_{max_i} - X_{min_i}} \tag{2}$$

The control variable's maximum and minimum values are X_{max_i}, X_{min_i}. FLC parameters refer to input and output gains K_i. For a better selection of these parameters.

Using Fuzzy Inference Rules, each input fuzzy value is assigned to its corresponding output value. This rule-based system is commonly used in artificial intelligence applications, such as automated decision-making and natural language processing. It is an effective way to handle uncertain data without requiring crisp values. Fuzzy Inference Rules are a powerful tool for extracting insights from fuzzy data. This assumption is based on a common concept: to stabilize the output around a set point, a large, small, or even zero control action is required. As shown in Table 1, the proposed controller involves two fuzzy variables for inputs and one fuzzy variable for outputs, each quantized into seven fuzzy sets. Fuzzy rules can be generated by off-line simulations, designers, engineers, or experts. It can be possible to gain knowledge about the dynamic system by understanding how it behaves [16].

Table 1 fuzzy rules of the proposed fuzzy Logic Controller

Δp \ $\Delta\omega$	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

A membership function is used to determine an output in ***defuzzification*** by using the maximum product and minimum maximum methods. Obtaining the output is achieved by applying a special rule to the membership function. The defuzzification of a fuzzy set is the process by which a crisp output value is found from its membership function. This can be done by calculating the maximum of the product of all the membership functions, or the minimum of the maximum of the membership functions. For each rule in the fuzzy controller, the output membership function is calculated using the minimum maximum method. In this system, real (nonfuzzy) signals are used for the generator excitation. In order to recover actual values from fuzzy values, the defuzzification process is necessary. This is achieved through the use of centroid defuzzification in the proposed controller**.**

4. Objective Function and Optimal Algorithm for Artificial Bee Colonies

The proposed Fuzzy Logic PSS controller is optimized with the ABC algorithm, using optimum scaling factors determined by the ABC algorithm. As inputs and outputs of FLPSS, speed deviations ($\Delta\omega$) and power accelerations (Δp) are assumed as inputs and changes in correction voltages (Δu) as outputs with associated scaling factors K_ω, K_p and K_u. In order to optimize fuzzy logic scaling factors, the integral of squared error (ISE) of generator speed deviation is formulated as an objective function. For the test system, Eq. (8) represents the cost function derived from ISE.

$$\begin{aligned} &J = \sum_{i=1}^{4} \int_{0}^{T_{sim}} |\Delta\omega_i(t)|^2 . dt \\ &{K_{\omega i}}^{min} \le K_{\omega i} \le {K_{\omega i}}^{max} \\ &{K_{pi}}^{min} \le K_{pi} \le {K_{pi}}^{max} \\ &{K_{ui}}^{min} \le K_{ui} \le {K_{ui}}^{max} \end{aligned} \tag{8}$$

Where i is the ith generator and T_{sim} is the simulation time. To obtain optimal input-output fuzzy logic scaling factors, ABC algorithm is used to minimize speed deviation.

In 2005, Karaboga discovered the Artificial Bee Colony Optimization Algorithm, a swarm-based search algorithm inspired by honeybee foraging behavior [14]. The algorithm is composed of three algorithms: Initialization, Swarm, and Localization. These algorithms work together to find the optimal solution to a problem. It is one of the most successful and widely used swarm-based optimization algorithms. This algorithm balances local and global optimal solutions within a short computation time. Thus, ABC is a powerful optimization technique for large and complex stability problems, such as power system stability that has a complex and changing structure.

In addition, ABC algorithm is flexible, short computational time, robust, easy to implement and tune, making it suitable for the practical implementation of complex power systems. The optimized problem can be solved with food sources. Several factors determine the quality value of food sources, including the amount of energy they provide, their proximity to nests, and the ease with which they can be harvested. The ABC flowchart is shown in Fig. 4 and the detailed steps are described as following:

At the beginning of the analysis, ABC algorithm generates an *initial population* of SN random D-dimensional vectors with SN representing the number of food sources. In the population, the ith food source is considered to be $X_i = (x_{i,1}, x_{i,2}, \dots, x_{i,n})$. As a result, initial food sources are generated as follows:

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

D is the number of parameters that have been optimized. The lower bound and the upper bound of are respectively x_j^{min} and x_j^{max}. In order to generate the initial population, three types of bees are used: employed bees, onlooker bees, and scout bees. In the first phase, employed bees X_i will generate new candidates' solutions V_i about their current positions. As a result, the new solution has the following position:

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

There must be a difference between K and i when $k = 1,2,3,\dots,SN$ and $j = 1,2,3,\dots,D$ are random indices. This difference is necessary to ensure that K is not confused with J, or that k is not mistaken for j in calculations. The difference between k and i must be significant enough to distinguish between the two indices. A $\emptyset_{i,j}$ value falls within the range $[-1, 1]$.

In the case of a parameter value exceeding its limits, the parameter will be set at its limit value. After that, the fitness value of candidate solution V_i will be compared to the fitness value of candidate solution X1. If the fitness value of candidate solution V_i is greater than X_i, the candidate solution (V_i) will be adopted, otherwise X_i will be retained. After the employed bees finish searching, the *onlooker bees calculate a food source probability* based on the following equation:

$$P_i = \frac{fitness_i}{\sum_{n=1}^{SN} fitness_i} \tag{6}$$

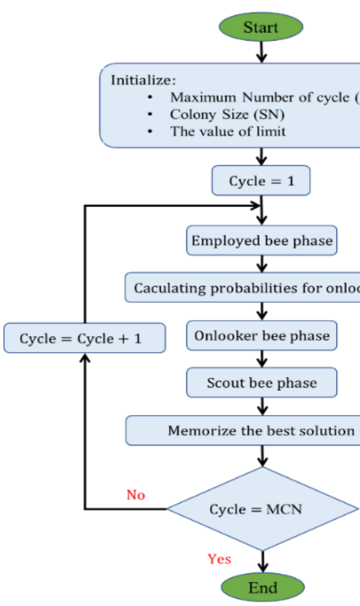

Fig. 4. ABC algorithm flowchart

Onlooker bees are more likely to choose a food source that is fitter. This is because fitter bees are more likely to be working, and thus more likely to be carrying the food. Onlooker bees also tend to be more tolerant of bees that are carrying the food, so they may be more likely to choose the same food source.

In the *Unemployed Bee Phase*, onlooker bees modify using Eq. (5) after being selected. The bee's new value is updated to consider its previous success rate. The bee will then use this modified value to compare with the values of other bees and decide whether to accept or reject them. If accepted, the bee moves to the active bee phase. In this case, the modified solution will replace the previous one if it has a fitness equal to or greater than the modified one.

The Scout Bee replaces a food source X_i if it can't be improved further over the limit L number of generations. As a result of Scout Bee activity, a new source of food is generated:

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

5. Simulation Results and Discussion

A multimachine power system with two areas, four machines, and eleven buses is tested to see if the proposed controller is effective. Essentially, the system is composed of two separate areas, as illustrated in Fig. 1, despite its small size, this system mimics the behavior of typical power systems in practice. The controller is used to regulate the voltage and frequency in the two areas. The controller is tested under various operating conditions, and the results are analyzed to compare the performance of the proposed controller with the existing control strategies.

A trial-and-error method is used to select initializing parameters, and after many attempts, the initial parameters were determined as follows: the population size (number of food sources) and employed bees are equal to 5, which equals the number of onlooker bees, and the optimization search process is terminated after 25 iterations. The parameter bounds for all input-output FLPSS scaling factors are considered the same as $1 \le K_{\omega i}$, K_{pi} ,$K_{ui} \le 3$. And the optimal set of input-output scaling factors using ABC algorithm are listed in Table 2.

Table 2 optimal set of input-output FLPSS scaling factors using ABC algorithm for two-area four-machine eleven-bus test power system.

Parameter \ Generator	G1	G2	G3	G3
$K_{\omega i}$	1.00	1.02	1.05	2.46
K_{pi}	1.67	1.37	3.00	1.31
K_{ui}	1.15	1.02	1.74	1.49

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

- Removing one of the two parallel transmission lines that connected the two areas.
- Adjusting the mechanical power input of Generator 3.

Each scenario simulates the steady state operation of the system from (0-1s) then introduces the disturbance at t=1s for (0.2s). Based on the disturbances described above, a comparison has been made between the proposed controller and a conventional power system stabilizer as proposed in [15], [18].

A. Removing one of the two parallel Transmission lines connected the two areas.

Simulations are conducted under a severe situation by permanently removing Line 1 between bus 7 and bus 8 that connects area 1 with area 2 in order to evaluate the proposed ABC-FLPSS controller. The system becomes extremely stressed as shown in Figures 5-9. As shown in Fig. 5, the power will flow through transmission line-2 after the fault occurs. In the proposed ABC-FLPSS, inter-area mode oscillations are handled more effectively, transient stability is improved, and power transfer capabilities are enhanced compared to CPSS.

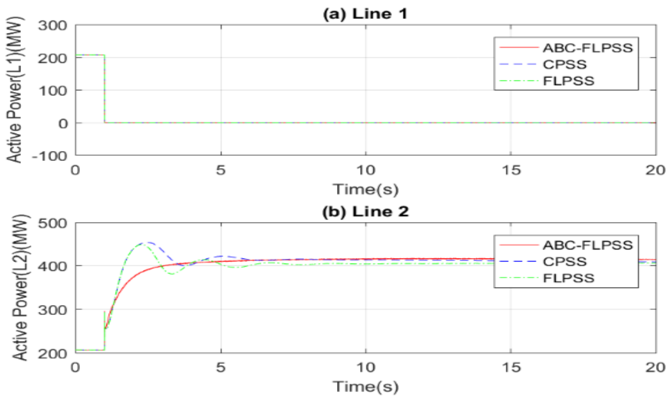

Fig. 5: Active Power Flow with removing Line 1 between bus 7 and bus 8

Fig. 6 shows terminal voltages when Line 1 between buses 7 and 8. ABC-FLPSS reaches an equilibrium point faster than other controllers (Fig. 7 and Fig. 8), with respect to the system's dynamic responses (terminal voltages, speed deviation, and rotor angle).

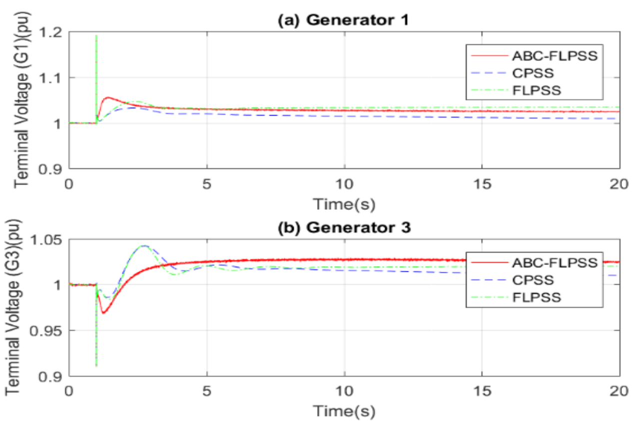

Fig. 6: Terminal Voltages with removing Line 1 between bus 7 and bus 8

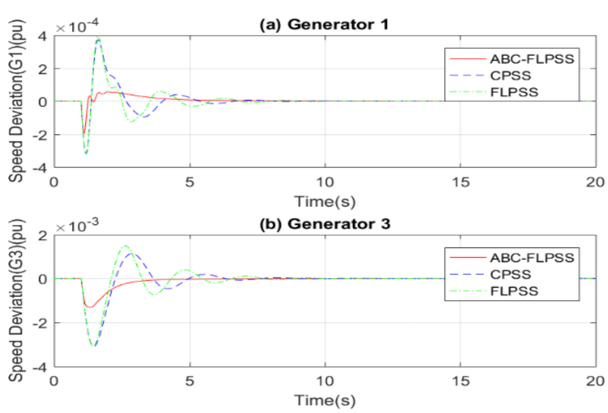

Fig. 7: Speed Deviations with removing Line 1 between bus 7 and bus 8

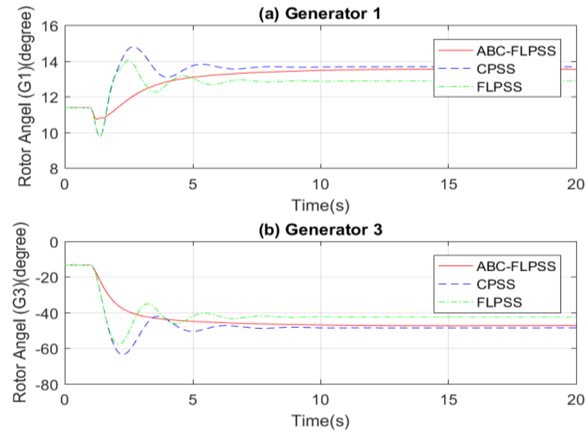

Fig. 8: Rotor Angles with removing Line 1 between bus 7 and bus 8

B. Adjusting the mechanical power input of Generator 3.

In order to maintain the desired output electrical power, the input mechanical power of the generators must be adjusted accordingly to ensure the stability of the power system. In this scenario, Generator 3 (G3's) input mechanical power is changed from 0.8 pu to 0.9 pu at T_{sim}=1s for a period of 10 seconds, then returned back to its nominal value at T_{sim}=11s. During practical operation, the electrical loads in the power system change, affecting the output electrical power of the synchronous generators. This affects the input mechanical power. Changing the nominal parameters of the power system will cause the system to operate at a different operating point. Fig. 9 shows that when the input mechanical power is changed, the terminal voltages of G1 and G3 shift to a new equilibrium point, and the ABC-FLPSS controller does a much better job damping oscillations than the other controllers. The CPSS response is very inefficient, and this is expected, because CPSS is designed around a specific equilibrium point and it will not behave correctly when this equilibrium point is modified. The ABC-FLPSS controller can respond quickly to changes in input power, thus providing a better damping effect. This is because the controller is designed around an equilibrium point that is variable and can be adjusted with the input power.

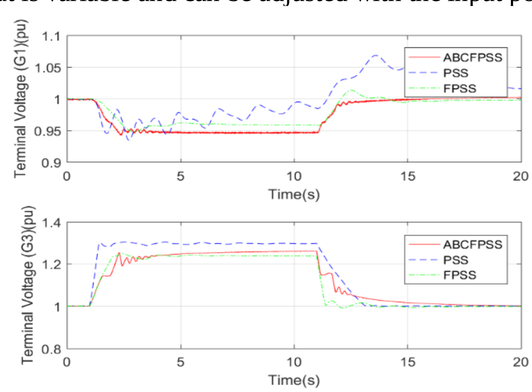

Fig. 9: Terminal Voltages with Changing the Input Mechanical Power of G3

In Fig. 10, we show the rotor speed deviations of G1 and G3. ABC-PSS is not comparable with CPSS in this scenario due to its slower convergence speed. The performance of ABC-PSS is also more stable than that of CPSS. This is because the control strategy of ABC-PSS is more adaptive and allows for more accurate prediction of the rotor speed. ABC-PSS is also better able to cope with changes in the system parameters. Additionally, G3 has a superior rotor angle response, as shown in Fig. 11, and the rotor angle settles to its new equilibrium point faster than the other controllers.

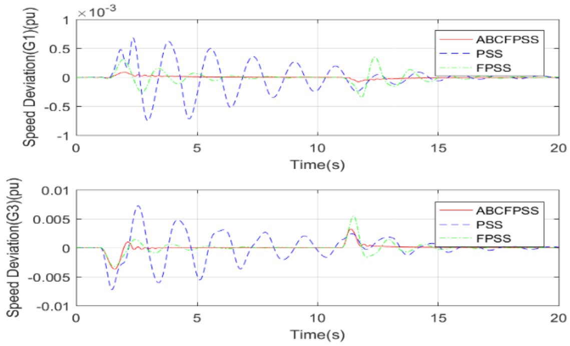

Fig. 10: Rotor Speed Response with Changing the Input Mechanical Power of G3

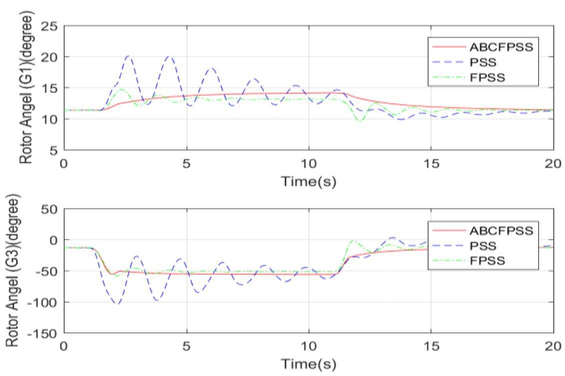

Fig. 11: Rotor Angle Response with Changing Input Mechanical Power of G3

6. Conclusion

Due to their ability to handle system uncertainties, fuzzy logic controllers are efficient for nonlinear dynamical systems. In contrast, classical controllers require an exact mathematical model and measurement. This paper proposed the ABC optimization technique to optimize fuzzy logic PSS input-output scaling factors to enhance multimachine power systems transient stability. Simulations of generator rotor angles and speeds were used to compare the proposed controller with conventional power system stabilizers. According to simulations, ABC-FLPSS damps power system oscillations and improves transient stability and robustness of multimachine power systems. The ABC-FLPSS controller has the potential to be applied in various real-world scenarios, such as power grids, renewable energy systems, and electric vehicle networks. By enhancing transient stability and robustness, it can contribute to the reliable and efficient operation of multimachine power systems, ultimately leading to improved power system performance and the prevention of blackouts. In summary, the paper concludes that the proposed Artificial Bee Colony optimization technique effectively enhances the transient stability and robustness of multimachine power systems. The ABC-FLPSS controller outperforms conventional power system stabilizers in damping power system oscillations and demonstrates superior and faster damping performance even under varying system operating conditions.

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