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Optimal Design of Damping Control of Oscillations in Power System Using Power System Stabilizers with Novel Improved BBO Algorithm

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ABSTRACT

Studies on power system stability are necessary for power network development & operation. Due to the great dimensionality and complexity of contemporary power systems, its significance has increased. The stability of an interconnected power system is seriously threatened by power system oscillation. Numerous strategies based on contemporary control theory, intelligent control, and optimization methods have been applied to the Power system stabilizers (PSSs) design problem recently. Each categorization contains a number of design techniques that increase the PSS's effectiveness and sturdiness in damping off low frequency vibrations. This work presents a new Modified and Improved Biogeography-Based Optimization (MIBBO) method to increase the optimization effectiveness of the usual Biogeography-Based Optimization (BBO) technique applied for the optimization of the parameters of the PSSs & Proportional Integral Derivative (PID) controller under the non-linear loading (NLL) conditions. The performance parameters which are obtained by the MIBBO based controller are compared with the results of normal BBO Method, Particle Swarm Optimization method (PSO) and Adaptation Law (AL) method. To justify the success and correctness of the proposed control approach, Matlab simulation results-based study of all the above-mentioned techniques is made and reported.

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1. INTRODUCTION

Common power quality problems include voltage harmonics, surges, spikes, notches, sag/dip, swell, imbalance, fluctuations, glitches, flickering, outages, and so forth. Due to numerous system disturbances or the presence of nonlinear loads like furnaces, uninterruptible power supplies (UPS), and variable speed drives, these problems may arise in the supply system [1]-[3]. In order to safeguard the system from power shortages, numerous power enrichment devices have been developed over time. PSSs and flexible ac transmission systems (FACTS) are two examples of oscillation damping controllers used in power systems [4]. Numerous studies have been conducted on the damping of low frequency oscillations in the power system. Power systems frequently employ PSSs to help reduce low frequency oscillations.

The PSSs modifies the automatic voltage regulator (AVR) by adding a stabilizing signal and modulating the generator excitation. A realistic PSS needs to be durable under a variety of operating settings and able to dampen the oscillation modes in the power system. Utility companies have embraced PSSs as a workable solution to improve power system dampening to low frequency oscillations in the region of 0.1 to 3.0 Hertz. An additional control block to improve system stability is thought of as a PSS's model. These oscillations can persist, expand, propagate across the system, and eventually cause the system to disconnect and collapse if not handled and controlled in a timely manner [5].

Low frequency oscillations that occur on their own frequently accompany changes in an electric power system's operational condition. It is obvious that power system features have a significant impact on the transmission line transfer capabilities and the stability of the power system. Most power system parameters, including bus voltage, line current, generator speed, and power, exhibit these oscillations. In addition to boosting transmission capacity, dampening oscillations is crucial for stabilizing power system conditions after serious breakdowns [6]-[7]. A power system's persistent low frequency oscillations are caused by the mechanical mode's lack of damping, and supplementary excitation control can deliver the needed additional damping. In general, the two basic classes of damping control techniques for power system oscillations are as follows: 1) Controlling damping at the sources of the energy, and 2) controlling damping in the transmission line. The effectiveness of oscillation damping has a significant impact on the effective and efficient operations of a modern power network. However, because damping controller development is a multimodal optimization issue with constraints, it is challenging to address with standard optimization techniques [8].

In order to manage nonlinear loads, converters, environmental effects, and power quality problems, multi-machine power systems require an optimal controller architecture. To achieve the necessary damping for power system stability, several automated damping systems are implemented [9]. The creation of damping controllers is an optimization problem that can be resolved by a number of methods. To prevent oscillations in power systems and assure safe operation, only a strong controller design is an option. But power system oscillations have a complicated character. Therefore, damping efficacy throughout various oscillation modes is examined to assure robust design. The most popular and well acknowledged optimization method for designing damping controllers is the use of heuristic algorithms [10]-[14].

Because of its simple design and dependability, conventional power system stabilizers (CPSS) are commonly utilized in utilities to address this issue. The PSSs settings can be tuned using a variety of methods. conventional techniques like gradient optimization and eigenvalue assignment. To overcome the drawbacks of the conventional methodologies, such as being a time-consuming problem, the sluggish convergence problem, and the solution obtained may not be optimal, evolutionary algorithms have been presented, such as Genetic Algorithm (GA), PSO [15]-[17].

Numerous investigations have been carried out using several conventional heuristic techniques. Heuristic algorithm performance is typically a problem-oriented application. Numerous heuristic approaches have been used in small-sized multi-machine systems (SMMS) and single-machine infinite-bus (SMIB) systems to examine the damping performance. It's critical to look into how design performance varies as problem dimensions (big power systems) increase. To reduce design complexity in certain instances, authors thought about using fewer controllers and optimizing certain parameters [18].

The new BBO algorithm for global optimization has demonstrated impressive performance on a number of well-known benchmarks. For BBO, there are still a few unresolved research issues that need to be resolved. In this study, we upgrade the BBO algorithm from the original BBO. The proposed MIBBO is made up of new strategies in order to further boost the performance and increase the exploration capability. Simulation is carried out using Matlab/Simulink software. The enactment of the proposed methodology is validated by matching the various parameters with the Conventional BBO technique, PSO technique & AL method. The results obtained clearly shows that the introduction of modification in the BBO method clearly improves the performance of the system under NLL conditions. The results are compared and discussed in the following sessions.

2. ANALYSIS AND MODELLING OF PSS

2.1. Design of PID based PSS

The purpose of PSS is to generate an additional stabilizing signal to align the electrical torque component with changes in speed [19]. In this study, the PID-based controller is used to design the PSS. The schematic of the PID controller-based PSS is shown in figure number 1. The synchronous machine's speed deviation ($\Delta\omega$) is the input signal provided to PSS. Through AVR and the excitation system, the synchronous machine receives the output signal of the PID-based PSS. The transfer function is depicted by the equation number (1).

$$V_{PID} = \left[K_P + \frac{K_I}{s} + s\,K_D\right] \Delta\omega(s) \quad (1)$$

Here, Δω indicates the change in the rotor speed.

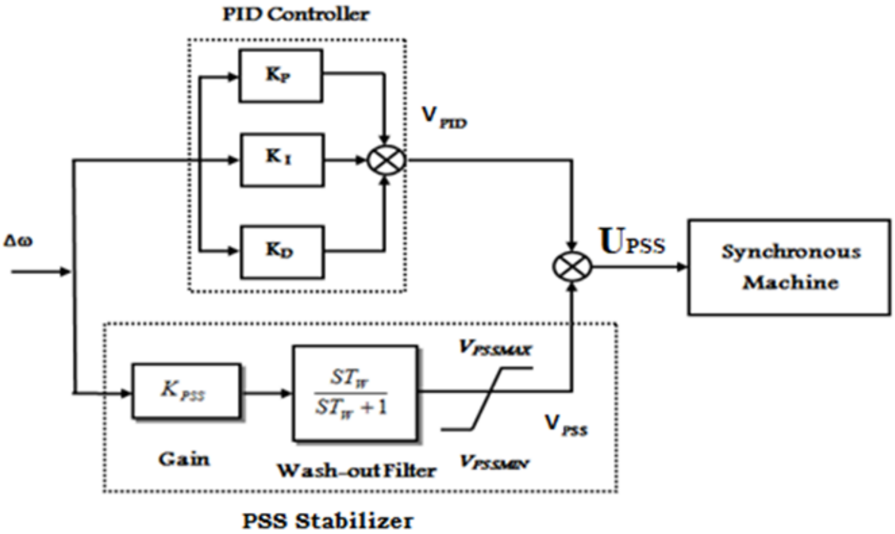


Figure 1. Schematic of PID controller-based PSS

The output of the PID_PSS i.e., U_{PSS} is given by the following equation (2).

$$U_{PSS} = V_{PSS} + V_{PID} \quad (2)$$

Here, V_{PSS} indicates the output of the conventional PSS.

The linear control theory is used to determine the parameters of conventional PSS (CPSS), which can be operated under specific conditions. Its shortcomings include time-consuming calibration and dampening that is subpar under other operating circumstances. The typical PSSs could not ensure appropriate damping during functioning of power network as it is non-linear in nature.

2.2. Formation of Objective Function

To achieve the best performance, the parameters of the coordinated PSS & PID controller should be tuned. The square of the integral of the error signal is taken into consideration in the role of objective function (OF) while determining the best parameter settings for the coordinated controller associated with a SMIB network [19]. The overshoot reduction and settling time are regarded as being highly essential factors in power system stability; therefore, it is crucial to design the system such that it settles quickly and oscillations end quickly. The major goals are to reduce low frequency oscillations (LFO) and improve system stability. Through minimalizing the OF i.e., square of the integral of the error signal of speed variations, this goal can be attained. The objective function for the SMIB network which is taken into consideration in this work can be denoted as below,

$$\text{ISE}, \min (J) = \int_0^{t_{sim}} \Delta\,\omega^2(t)dt \quad (3)$$

Here, t_{sim} denotes the simulation time.

It is intended to reduce the goal function in order to preserve stability and offer effective dampening. With the aforementioned goals in mind, this study work uses the BBO algorithm and MIBBO algorithm that has been suggested to minimize the objective function while subject to restrictions and to find the coordinated controller's best control parameter values. Additionally, the performance of the system using optimized values acquired from the proposed Algorithm is contrasted with the performance of the system using optimal values derived from other optimization algorithms such PSO & AL methods.

3. CONTROL STRATEGIES USED IN PSS

3.1. Description of the BBO Algorithm

Based on Dan Simon's history, a new population-based evolutionary computation technique was released in 2008 [15]. The BBO algorithm model describes how species move between islands, giving rise to set of newfangled species, & how few others groups eventually die nonexistent. Habitat Suitability Index (HSI) identifies the ideal habitat aimed at a group, taking into account factors such as vegetation diversity, rainfall, temperature, and land area. A high HSI island or habitat is thought to perform well on optimization problems, while a low HSI island or habitat performs poorly. The suitability index variable (SIV) refers to the quantity of features in each habitat [20]. The SIV density reflects the problem dimension in each environment. HSI is regarded as the dependent variable, while SIVs are the independent variables. As illustrated in Figure number 2, the island which has a high HSI value will have the greater emigration & smaller immigration rates, and the opposite is true for an island with a low HSI.

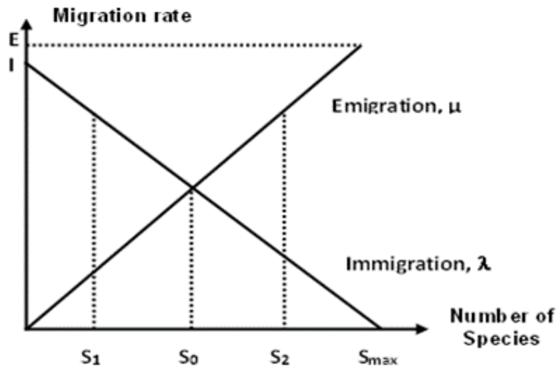


Figure 2. Change in Emigration & Immigration

3.1.1. Migration Process

The ability to migrate between habitats can be realized, and after that, the operator can search the entire problem space. In BBO, the solution vector is derived from a population of solutions. SIV is used to compute the habitat suitability index (HSI), which indicates how excellent or terrible the habitat is (solution). The likelihood of information sharing among the habitats is determined by the emigration and immigration rates of the solution [21]. The elitism procedure is used to prevent the best solution from migrating during the immigration process. The graph in Figure 2 can be used to determine the immigration and emigration rates. They are given by the following equations.

$$\text{Emigration rate}, \mu = \frac{E_m S_0}{S_{max}} \tag{4}$$

$$\text{Immigration rate}, \lambda = I_m \left(1 - \frac{S_0}{S_{max}}\right) \tag{5}$$

where, E_m – Maximum Emigration Rate

S_o – Number of species at equilibrium

S_{max} – Maximum number of species

I_m – Maximum Immigration Rate

3.1.2. Mutation Process

In nature, illnesses or natural disasters can alter a habitat's ecological environment, and as a result, that habitat's HSI will quickly shift. To simulate this scenario, the BBO algorithm uses the mutation operator and modifies the HSI in accordance with the probability of species quantity. The mutation rate is computed using the species count probability. Elitism has been utilized to preserve the characteristics for the territory with the optimal PID & PSS estimates during this process, allowing us to go back to the original state even if a mutation destroys the habitat's HSI. The habitat's mutation probability ‘m’ is written as follows.

$$m = m_m \left(1 - \frac{P_S}{P_{max}}\right) \tag{6}$$

where, m_m – Maximum Mutation Probability

P_S – Probability of each island containing S species

P_{max} – Maximum probability of species quantity

3.1.3. BBO Algorithm

Each habitat in the SMIB scenario that offers a potential solution is made up of SIVs [22].

Step 1: Create a random set of habitats (a possible solution) after setting the BBO parameters to their initial values. Habitat set H is a representation of a full solution vector made up of the set of SIVs for each habitat H_{ij}. Equation (7) give the matrix of habitat set H of BBO for optimal tuning. The habitat vector is represented as H_{ij}, where i=1, 2, ..., N and j=1, 2, ..., m. The number of SIVs is m, while the number of habitats is N.

$$H = \begin{bmatrix} K_{P1} & K_{P2} & \cdots & K_{PN} \\ K_{I1} & K_{I2} & \cdots & K_{IN} \\ K_{D1} & K_{D2} & \cdots & K_{DN} \\ K_{PSS1} & K_{PSS2} & \cdots & K_{PSSN} \\ T_{11} & T_{12} & \cdots & T_{1N} \\ T_{21} & T_{22} & \cdots & T_{2N} \end{bmatrix} \tag{7}$$

Step 2: For each habitat, determine, μ and λ, the cost function, and the HSI; then, based on the HSI value, map each habitat to its corresponding μ and λ.

Step 3: Based on the HSI value, choose the best habitat and preserve it. If the habitat H_{ij} has the highest V_{PID} and V_{PSS} values, it is regarded as an elite habitat. The initial "p" elite habitats are shielded from change in subsequent rounds.

Step 4: Using the migratory process, probabilistically alter the non-elite environment using μ and λ.

Step 5: After mutating the non-elite environment based on the species count probability of each habitat and move on to step 3.

Step 6: This loop is ended after a predetermined number of iterations.

After each habitat has been modified (steps 2, 5 and 6), its viability as a candidate solution should be evaluated, and if it is not, factors should be calibrated to make it one.

3.2. Description of the MIBBO Algorithm

One of the problems with the normal BBO algorithm is that, it is simple for the algorithm to enter the local optimal, so as to reduce the BBO algorithm's capacity for exploration. In order to address the aforementioned local optimization and further investigate the potential of the method, this research extend the BBO and provide a new and improved version of the algorithm called MIBBO.

The steps 1 through 6 of the improved BBO algorithm are the same as those of the traditional BBO, with the exception of step 3. In step 3, the user initializes the elitism parameter 'p' with the desired number of elite parameters to be preserved. Based on the number of species in the newly created H_i, S_{inew}, the improved BBO's p is calculated. Thus, the elitism parameter is calculated using the enhanced BBO algorithm as in Equation (8). The elitism parameter is varied in each iteration rather than remaining constant during the execution of this method, which improves optimization. Figure number 3 displays the flowchart for the Improved BBO algorithm, which is used to adjust the PID and PSS damping controller's parameters.

$$p = \frac{N-i}{S_{inew}} \tag{8}$$

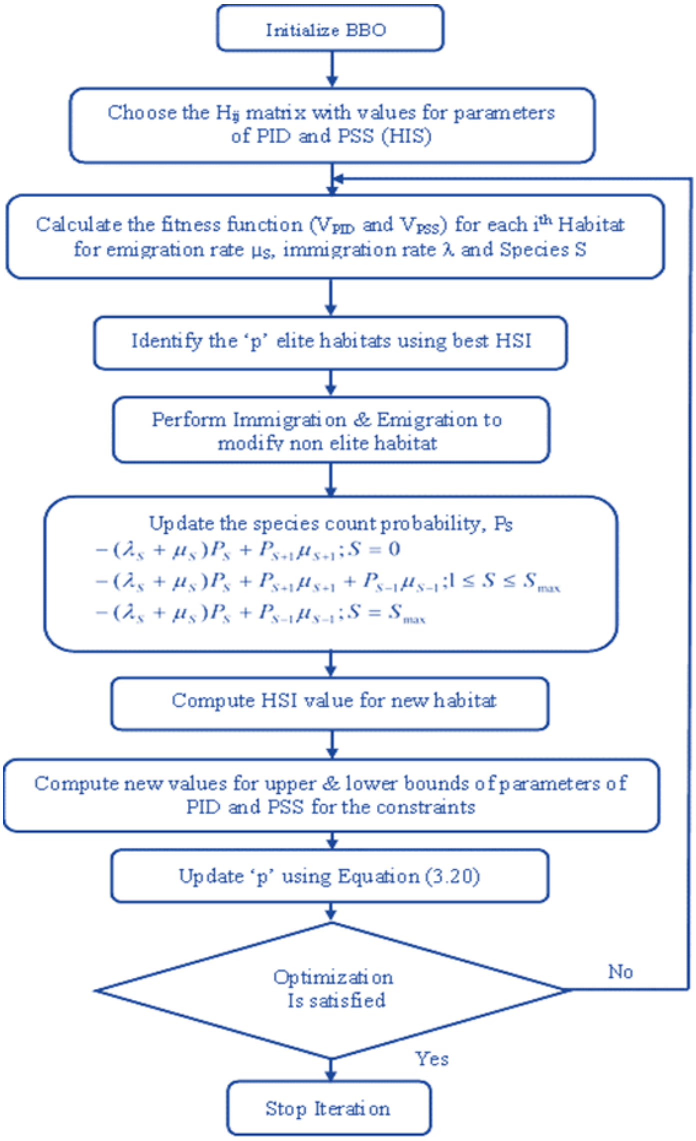


Figure 3. Flowchart of MIBBO for PID-PSS

4. SYSTEM UNDER CONSIDERATION

For the study of proposed designs, the single machine infinite bus (SMIB) power system is taken into consideration in this section. Figure number 4 depicts the SMIB system, which consists of an 11kV/132kV transformer and a 300MW generator. Tables 1 & 2 provides the system data and loading circumstances used for the analysis [16]-[17].

The blocks Synchronous Machine, Hydraulic Turbine & Governor, Exciter & Automatic Voltage Regular (AVR), and Transformer, among others, were used to create the Simulink model of the SMIB system. Through exciter & AVR block, the coordinated damping controller (PIDPSS) was shunt-connected to the synchronous machine. In order to examine the performance during nonlinear case studies, a 3-phase 6-pulse thyristor converter-based non-linear load was constructed in the Simulink environment and subjected to the SMIB system. The transmission line was subjected to various operating situations including base load, heavy load, ground fault, and 3-phase fault. According to the Transmission System Reliability Standard (TSRS Version 2, Edition 01, Jan 2006) of Tenaga Nasional Board (TNB), Malaysia, a problem enters the system at 0.01 s & it is released subsequently at 0.1 s [16]-[17], [19].

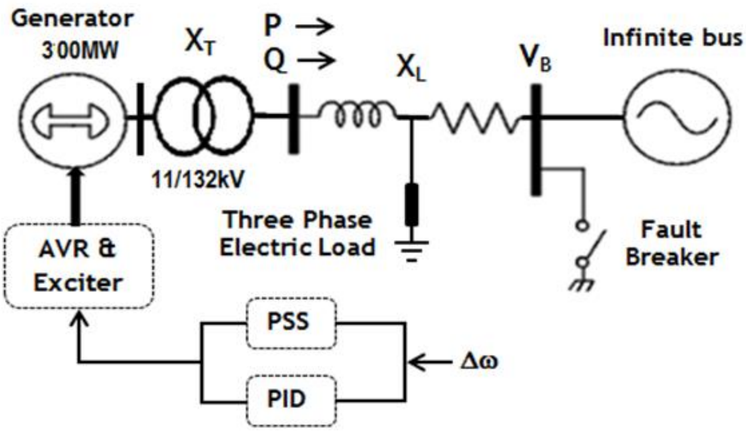


Figure 4. A line diagram of SMIB network

Table 1. Parameters of the System

Alternator	$f = 50Hz, X_d = 1.3p.u., X_d^{'} = 0.34p.u., X_q = 0.474p.u.,$ $T_{d0}^{'} = 1.07s, P = 300MW$
Line & Transformer	$11/132\ kV, 50Hz,\ X_T = 0.131p.u. X_L = 0.6p.u.$
AVR, Exciter & PSS	$K_A = 300, T_A = 0.001s, K_E = 1, K_F = 0.5, T_3 = 3s, T_4 = 5.4s, T_W = 5s$

Table 2. Load conditions considered

Base Load	P = 65 MW, Q = 10 MVAR
Heavy Load	P = 195 MW, Q = 30 MVAR

The schematic of the proposed methodology for MIBBO algorithm based PID-PSS controller is shown in the figure number 5.

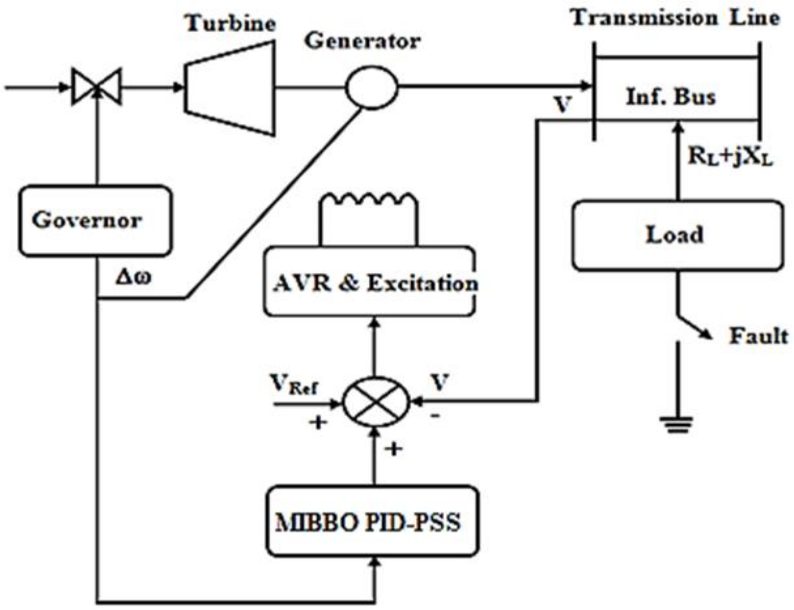


Figure 5. Schematic of SMIB power system using MIBBO based PID-PSS

5. SIMULATION RESULTS AND DISCUSSIONS

In order to prove the effectiveness of the proposed control method, simulation studies are done using MATLAB/SIMULINK and the outcomes are reported. After that, the suggested methodology is evaluated with the help of SMIB network with a 3-phase thyristor-based NLL condition accompanied by a severe fault condition with the purpose of scaling its robustness. Table 2 displays the typical parametric ranges for the PID-PSS controller that were optimized using the IBBO algorithm. Two different cases are utilized for the simulation purposes, one with NLL & Ground fault and the other NLL & 3-phase fault.

Table 3. PID-PSS Parameter Ranges for MIBBO Method

Parameters	Parameter Limits
K_P	$0.5 \leq K_P \leq 80$
K_I	$0.2 \leq K_I \leq 30$
K_D	$0.1 \leq K_D \leq 15$
K_{PSS}	$1 \leq K_{PSS} \leq 60$
T_1	$0.2 \leq T_1 \leq 2$
T_2	$0.2 \leq T_2 \leq 2$

Situation 1: NLL including ground fault

This study is done in light of the system's stability (Figures 6 through 8). In this case study, the graphs illustrate the discrepancy between the speed variations, rotor angle variations, load angle, and field voltage pertaining to time. In contrast to PSO, adaptation law, and CPSS, the system reaches the steady state quickly with an overshoot of about 0.01 per unit.

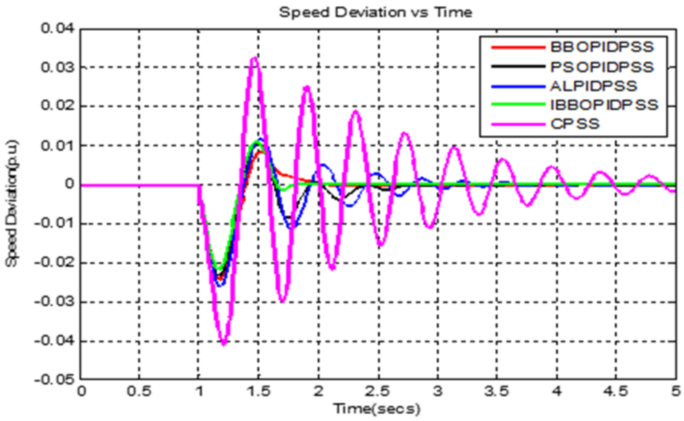


Figure 6. Graph of Speed Variations using different Controllers

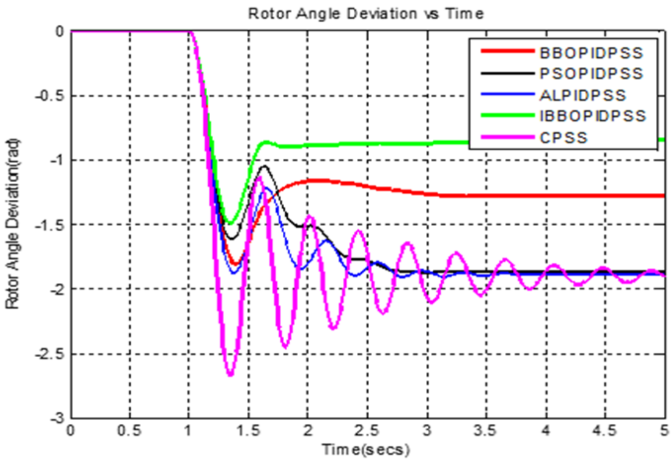


Figure 7. Graph of Rotor angle Variations using different Controllers

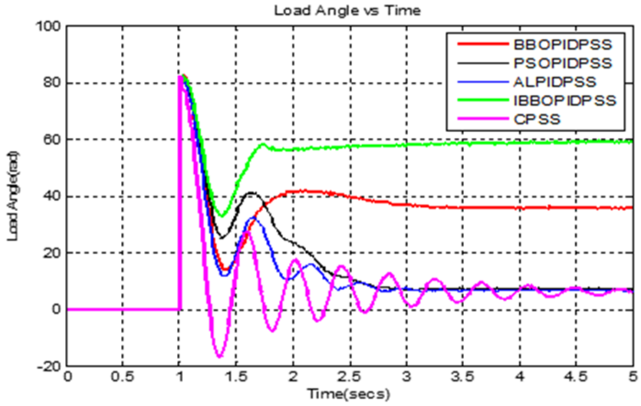


Figure 8. Graph of load angle using different Controllers

Situation 2: NLL including a 3-fault

The stability of the system in risky circumstances is explained by this case. The transmission line was thought to be the site of a three-phase problem. At 1.01 seconds, the error entered the system, and at 1.1 seconds, it was fixed. Figures 9 through 11 show how the synchronous machine in this case study performed. Figure 9 shows that the system settles in around 2 seconds and the proposed damping controller results in less overshoots.

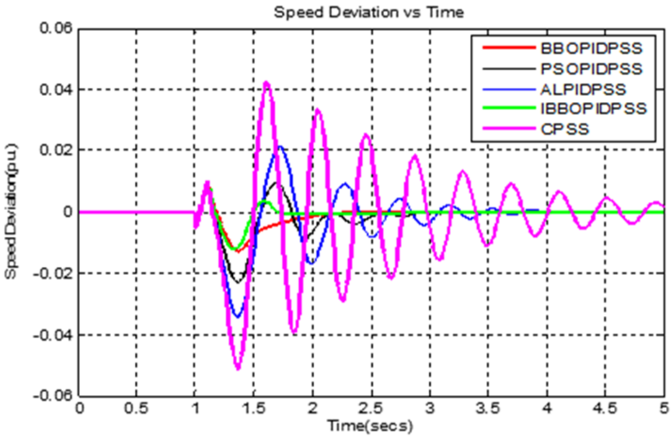


Figure 9. Graph of Speed Variations using different Controllers

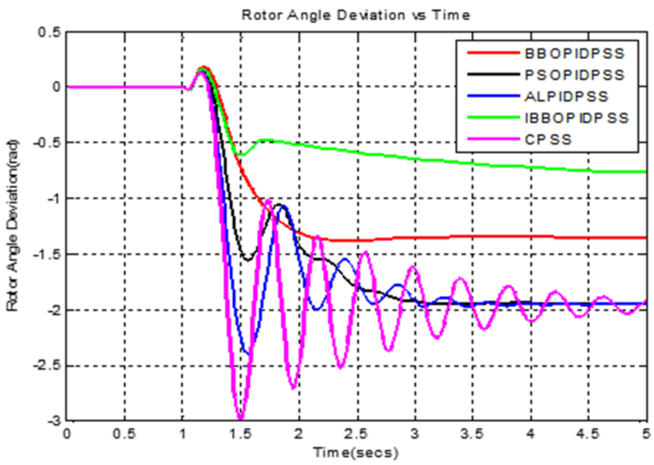


Figure 10. Graph of Rotor angle Variations using different Controllers

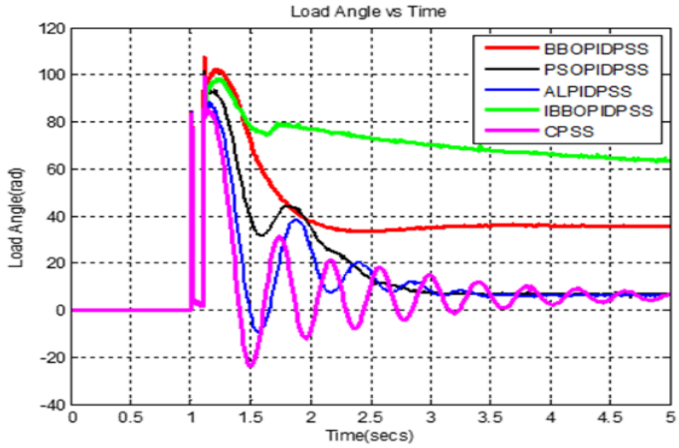
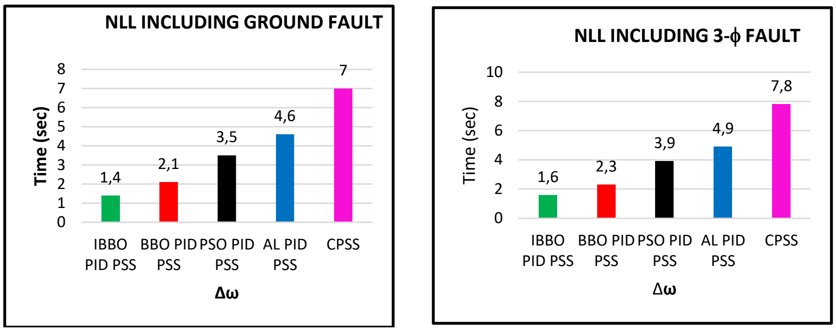


Figure 11. Graph of load angle using different Controllers

The investigation shows that the suggested damping controller keeps a synchronous machine running at synchronous speed even when there is substantial fault damping. The coordinated controller's speed deviation settling times for various methods under nonlinear load and various fault scenarios are compared in Figure 12 (a) and (b). In the case of a non-linear load with a ground fault, the settling times are 1.4s, 2.1s, 3.5s, 4.6s, and 7s for IBBO, BBO, PSO, AL, and CPSS, respectively. When using a non-linear load with a 3-phase fault situation, the settling times are 1.6s, 2.3s, 3.9s, 4.9s, and 7.8s for BBO, PSO, AL, and CPSS, respectively. Under non-linear load with a 3-phase fault situation, settling time is decreased by 30.4 percent in IBBO compared to BBO, 59 percent compared to PSO, and 79.4 percent compared to CPSS.



(a) **(b)**

Figure 12. Settling time for Speed Variations using different Controllers

Table 4. PID controller Values using different Controllers

Methodology Used		**PID Values** K_P	K_I	K_D	**Performance Index (J)**
MIBBO Method		67.2	26.4	15	5.23
BBO Method		52.6	20.2	9.73	6.24
PSO Method		5.14	0.9	1.63	23.41
AL Method	NLL including Ground Fault	0.2725	0.6264	32.42	-
	NLL including 3-ϕ fault	0.5734	0.4264	31.58	-

Table 5. PSS Values using different Controllers

Methodology Used	PSS Values K_{PSS}	T1	T2	Performance Index (J)
MIBBO Method	26.68	0.6	0.11	12.23
BBO Method	31.7	0.80	0.38	16.4
PSO Method	74.65	1.87	0.074	23.41
AL Method	125	5000	2000	-

Tables 3 & 4 display the values of the PID-PSS controller as determined by three different techniques.

6. CONCLUSION

The major goals of this research are to reduce the low frequency electro-mechanical oscillations & improve stability of SMIB network during serious shocks. The coordinated design of a PSS damping controller that is based on PID is highly sought in order to enhance the dynamic performance of the system. In this work, a single machine infinite bus power system is taken into consideration and used under various load scenarios. The coordinated controller was modelled in a SIMULINK environment to test its efficacy, and after that, its performance was compared to that of other controllers. The elitism parameter is varied in each iteration rather than remaining constant during the execution of this method and the enriched MIBBO algorithm is used in this study to improve the algorithm's ability to explore new areas and speed up convergence rate. The performance of the enhanced MIBBO algorithm was then evaluated and compared to that of the standard BBO and other optimization techniques. When improved BBO (MIBBO) was implemented, it was found that, NLL including ground fault case, and NLL with 3-phase faults, the settling time of the MIBBO-based coordinated controller was reduced by 76.7 percent, and 78.9 percent correspondingly.

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