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Designing a power system stabilizer using a hybrid algorithm by genetics and bacteria for the multi-machine power system

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ABSTRACT

This research creates an optimal power grid stabilizer for four machines. Rotor speed signals are system inputs in the proposed design. To improve response, this system uses a conventional power system stabilizer (CPSS) and an optimal CPSS (OCPSS). The genetic optimization hybrid has a new structure, and the network generators use the bacterial foraging algorithm (BFA) with stabilizer system. The system set is tested by MATLAB software under various conditions to evaluate the designs. The experiment starts with a three-phase fault in line 3 that is fixed by breaking the line after 0.2 seconds. The simulation results show that after a short circuit in line 3, the proposed OCPSS design reaches damping after about a cycle of oscillation in 4 seconds. However, the conventional CPSS design achieves damping after four oscillations in six seconds. Simulations show that the proposed method is better than genetic algorithm (GA) and BFA. Power system oscillations are dampened faster and with lower amplitude when power system stabilizer (PSS) coordinate with the proposed optimization method. It also improves power system dynamics. We demonstrate with the proposed OCPSS stabilizer that advanced optimization systems can maximize system control capacity by utilizing conventional CPSS system advantages.

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NOMENCLATURE

i	Number of bacteria	*β(i)*	1or–1
£(j)	A random direction unit length between (0, 1)	*D*	Simulation dimension
S	Total population of bacteria	ωrep	The width of the repellant effect
Δ(i)	A random number on (0, 1]	*Pe.d*	Probability of dispersal
J	Chemotactic step number	*P(i, j, k)*	The location of each bacterium
JCC(θ)	Operator of swarming bacteria	*ϒ(i)*	Cost function
k	Reproductive step number	*Nr*	Maximum number of reproductions
Θim	The mth component of the ith bacterium, position θi	*Ned*	Maximum number of eliminations and dispersals
l	Elimination and dispersal step number	*Sr=S/2*	Half of the bacterial population

Datt	The depth of the attractant released by the cell	*C(i)*	Chemotactic step size
hrep	The height of the repellent effect	*Ns*	Swimming length after tumbling of bacteria
θ	Bacterium position	*Nc*	Number of iterations in a chemotactic loop
ωatt	The width of the attractant signal	*Jhealth*	Ascending cost of the bacterium
p	Number of parameters to be optimized		

1. INTRODUCTION

Electromechanical oscillations between interconnected synchronous generators in power systems are an inherent phenomenon. Damping of these fluctuations is an important issue, and is a basic condition to ensure proper system performance. Power system stabilizer (PSS) inject additional generator excitation control signal in the excitation circuit to dampen these oscillations and improve the system's dynamic performance [1]–[14]. Robust PSSs need to provide satisfactory results over a wide range of operating points. In recent years PSS designs using nonlinear controllers and artificial intelligence (AI) methods, such as neural networks and Fourier transform [15], fuzzy logic (FL) [16], adaptive neuro-fuzzy [17], and fuzzy auto-regressive moving average (farm) model [18] are common approaches to overcome the shortcomings of conventional (CPSS) other AI techniques and evolutionary algorithm (EA) with a higher degree of robustness and adaptability such as genetic algorithm (GA) [19], particle swarm optimization (PSO) [20], bacterial foraging algorithm (BFA) [21], EA [22], ant colony optimization (ACO) [23], [24], simulated annealing (SA) [25], tabu search algorithms (TSA), and chaotic optimization algorithms (COA) [26] have also been used to optimize CPSS parameters and to achieve better damping. According to Zadehbagheri *et al.* [27] optimal tuning of an FL power system stabilizer using the PSO method is carried out.

Most conventional PSSs in electrical power systems use the linear control theorem to achieve a linear model of a power system under certain conditions and constant coefficients in operation [4], [7], [9], [10], [28]–[34]. A CPSS with constant parameters, which is widely used in power systems, has many problems in setting its coefficients. Also, due to the complexity and non-linearity of the power system, the use of numerical methods and the classics make it difficult to solve the problem [27]. These conventional systems usually consist of control sections or proportional integral derivative (PID) controllers [32], which are also resistant due to their simplicity. But there are problems with properly adjusting their coefficients. CPSS with fixed parameters can ensure its stability in a wide range of system loading conditions, but if the CPSS parameters are not set well, it cannot have the same acceptable quality as the original performance, especially when changing the system operating point [35]. In order to solve these problems, adaptive stabilizers have been introduced based on the adaptive control method. These stabilizers improve dynamic performance under a variety of operating conditions. Nevertheless, the main problem with these stabilizers is the need to properly detect the system parameters, allowing immediate viewing of the system state [36]. If these parameters are not well estimated in different operating conditions, it reduces the performance and stability of the stabilizer at run-time.

In recent years, FL has been introduced as a powerful tool, and its use has begun in various applications in the power system [37]. From this new logic inspired by human decisions, one can design a controller using the results of linguistic rules without knowing the model of the system, which makes FL controller systems attractive with unrealistic parameters. However, it should be noted that these systems are becoming more complex, and as a result, their operating costs are increasing. This issue can delay or even eliminate the industrialization of a method with all its precision and high efficiency. Methods for the optimal design of conventional PID controllers are carried out in various systems, which have achieved good results [37]. as it can be achieved with the least complexity of a controller.

GA is one of the most popular bio-inspired optimization methods and has been used in various cases for many years [38]–[42]. This algorithm, which follows Darwin's theory of "survival of the fittest," is not always accurate in all cases, so different algorithms were presented after that. Moreover, in many cases, models of combinations of several algorithms were also studied. One of these new optimization methods that has everyone's attention is behavior-based bacterial search [43]. The bacteria foraging optimization algorithm (BFOA) [44], [45] is an evolutionary computational method. In this scheme, a type of bacterium called *E. coli* in the human gut is imaged from search behavior (methods for locating, transporting, and searching for food). This behavior undergoes various steps, such as chemical reactions, swimming, reproduction, removal, and dispersal. At the stage of the chemical reaction, the bacteria can make a false move in one direction. When swimming, each bacterium begins by swimming in one direction through signals from other bacteria. Furthermore, in the multiplication of the weakest bacteria and the division of the healthiest bacteria into two halves, these also replace the same dead bacteria. In addition, in removing and dispersing, each bacterium can be scattered based on the probability of its location and placed elsewhere within the optimization region.

The application of intelligent meta-heuristic methods for controlling complex and nonlinear systems has been widely used in various fields of science and technology in the last decade [46]–[54]. Sometimes, such problems can have a very complex objective function or model constraints, depending on their actual and practical nature. Such methods are powerful, and their effectiveness in solving various types of optimization problems has been proven [55]. A huge amount of literature is available on non-traditional optimization tools. These methods include, genetic programming (GP) [55], evolution strategies (ES) [56], differential evolution (DE) [56], cultural algorithm (CA) [57], evolutionary programming (EP) [57], whale optimization algorithm (WOA) [24], grasshopper optimization algorithm (GOA) [58], kidney-inspired algorithm (KA) [58], salp swarm algorithm (SSA) [58], sine cosine algorithm (SCA) [59], bat algorithm (BA) [59], general relativity search algorithm (GRSA) [60], farmland fertility algorithm (FFA) [61], artificial bee colony (ABC) [62], cuckoo search optimization (CSO) [63], interior search algorithm (ISA) [63], teaching-learning-based optimization (TLBO) [64], harmony search (HS) [64], biogeography-based optimization (BBO), seeker optimization algorithm (SOA) [65], moth search algorithm (MSA) [66], hybrid pattern search–sine cosine algorithm (HPS-SCA) [67], modified version of multi-objective particle swarm optimization (MOPSO) [68], MSA [68], gray wolf optimization (GWO) [69], hybrid of genetic algorithm and pattern search (GA–PS) [68], brainstorm optimisation algorithm (BSOA) [70], asexual reproduction optimization (ARO) [70], and others were developed for multi-machine PSSs design.

PSS is one of the most convenient and inexpensive methods to improve the dynamic stability of power systems. PSS provides a suitable control signal to increase damping and thus increase the transmission power of the lines. CPSS contains several parameters that must be specified during the design phase, and their precise adjustment has a great impact on the performance of power systems [71]. CPSS parameters are usually calculated and determined using various methods. However, power system structure and changes in system loading conditions can affect CPSS performance by damping all modes, especially inter-region oscillations. Good research has been done in this area in recent years to overcome this problem and have a suitable optimal power system stabilizer. In these studies, different methods have been proposed to design CPSS parameters. By increasing the PSS's performance, it can act well against power system fluctuations and dampen them.

In the following, we will discuss the latest optimal methods presented in recent years for PSS design [71]. Research by Guo *et al.* [72] an analytical method for finding CPSS parameters such as washout signal and operation is presented. According to the obtained results, it can be concluded that by properly adjusting the CPSS parameters, it can work well in a wide range of system conditions. Research by Guo *et al.* [72] the focus is on distributed excitation control for multi-machine power systems. The proposed distributed power system stabilizer (DPSS) aims to synchronize all generators after being disturbed rather than require them to operate at their rated speed. The proposed DPSS is analyzed on a double-machine infinite bus system and shows that the proposed DPSS can enhance the stability of power systems by increasing the synchronizing torque.

According to Reddy and Kishore [73] the structure of a robust PSS using a fuzzy-type PID controller optimized with a firefly algorithm (FA) to increase the dynamic stability of the power system is proposed. Optimization by FA overcomes the convergence problem in GA and PSO. FA requires several parameters to adjust and produces faster results than other computational methods. Research by Reddy and Kishore [73] the BSOA is described as a novel, promising heuristic optimization algorithm inspired by the brainstorming process in human beings. In this paper, BSOA is employed to find the optimal location and setting of flexible AC transition systems (FACTS) devices. Based on the brainstorming process in human beings, BSOA is proposed for solving optimization problems. In BSOA, individuals are analogous to ideas in brainstorming, clusters are analogous to brainstorming groups, and cluster canters are analogous to the best ideas of brainstorming groups. BSOA leads to a better voltage profile and lower losses than other optimization methods.

According to Marco and Rullo [74] the dominant pole spectrum Eigen solver algorithm and the integral of square time multiplied square error (ISTSE) criterion as the objective function were used for the optimal design of the power system stabilizer in a two-area standard power system. According to Suresh and Meenakumari [75] an innovative algorithm called HPS-SCA is proposed to determine the lead-lag stabilizer parameters online. In this paper, fitness is a function of eigenvalue displacement. The optimization algorithm determines the decision variables in such a way as to ensure that the eigenvalues are within the allowable range in different operating conditions. Research by Okafor and Longe [63] the hybrid BFOA-PSO algorithm has been applied to the IEEE 14 bus test system under normal, light, and heavy load conditions. BSO combines both algorithms, BFOA and PSO, thus using the advantages of both techniques. The aim is to make use of PSO's ability to exchange social information and BFOA's ability to find a new solution by elimination and dispersal.

According to Reddy and Kishore [73] a MOPSO is proposed for the optimal design of the stabilizer of lead-lag PSSs. Research by Suresh and Meenakumari [75] the neural network is used to design the PSS. One of the problems of neural network applications, which is mentioned in this article, is the long training time of the network as well as the difficulty of selecting the number of layers and neurons. As a result, in some articles, including [66], a fuzzy controller has been used for this purpose. Given that the design of the fuzzy controller does not require complete specification of the model, it is very efficient in practice. Research by Suresh and Meenakumari [75] an adaptive fuzzy sliding-mode controller is provided with the help of a PI controller for damping power system oscillations. In this study, a neural network based on the wavelet transform function was used. Research by Wang *et al.* [64] the bacterial foraging optimization method has been used to adjust the stability coefficients of the power system. A combined method of bacterial optimization of the particle algorithm has been used. The GOA is also used for this purpose.

In this paper, a sequential combination of this algorithm and GA is presented to determine the coefficients of a CPSS. The combination of these two types of algorithms has been done in other articles for various applications. However, in the proposed structure of this article, this combination is complete and sequential. Research by Faraji *et al.* [45] for example, only mutation and integration operators of some GA are used. The proposed design uses a GA with binary codes and a higher optimal zoning speed. In this article, we will first give a descriptive review of the GA and the BA. which will be explained in the continuation of their sequential combination design. In the next section, the network and stabilizer system are shown, and then the simulation results are examined under different operating conditions.

2. HYBRID GENETIC ALGORITHM AND BACTRIAL FORAGING ALGORITHM

The BFA method is an evolutionary optimization technique that is inspired by the exploratory behavior of the *bacteria E. coli.* Biological aspects of bacterial exploration methods and their movement behavior. In addition to their decision-making mechanisms, they can be found in [55]. As an exploratory method, the BFA method is designed to overcome the problems of gradient-free optimization and to deal with complex and non-differentiable objective functions. In the BFA method, tumbling with a single length is represented in a random direction (j), which determines the direction of movement after tumbling. The unit length constant C(i, j) indicates the size of the step taken in the random direction. Recently, the search and optimal nutrition of bacteria have been used to solve optimization problems. The joint search function of an animal requires communication facilities, and in a period of time, it can use the facilities of observing the whole group. Over some time, this increases the benefits that it can take advantage of by allowing it to see the whole group. This behavior helps the group catch more extensive prey, or alternatively, members can have better support in terms of catching in the group. The overall function of this bio-inspired algorithm comes from the search behavior of the bacteria to find nutrition, which sometimes it has done collectively. The principles of moving bacteria are innovative and toward more food; eventually, the bacteria that get enough food will survive [73]. The survival of species in any natural evolutionary process depends on the criterion of their appropriateness, which is itself based on motor behavior and food search. The law of gradual evolution supports species that have the ability to search for better food and eliminates or deforms those that have the ability to search less. Stronger species genes are propagated in the evolutionary chain in later generations due to their ability to reproduce even better species. Therefore, the correct understanding and modeling of exploration behavior in each of the evolutionary species leads to the possibility of applying it in any nonlinear system optimization algorithm [75]. The control system processes of these bacteria, dictating how foraging should occur, can include chemotaxis, swarming, reproduction, and elimination and dispersal [66].

2.1. Chemotaxis

Characteristic of the bacterial movement in search of food can be defined in two ways: swimming or tumbling, which is called the combination of these two movements chemotaxis. Depending upon the direction of rotation of the flagella in a bacterium, it either moves in a predefined direction (swimming) or changes its direction (tumbling). Mathematically, the rotation of any bacteria can be denoted by the unit length of a random motion $\varphi(j)$ multiplied by the step length of that bacteria C(i). In swimming mode, this random length is predetermined.

2.2. Swarming

In order to model cell-to-cell signaling via an attractant and a repellent that operate upon swarming bacteria, the function $Jcc(\theta)$, i=1, 2, ... S is represented by (1).

$$Jcc\big(\theta, P(j,k,l)\big) = \sum_{i=1}^{s}\big[-datt \exp\big(-\omega att.\sum_{m=1}^{p}(\theta m - \theta^i m^1)^2\big)\big]$$

$$+\sum_{i=1}^{s}\left[hrep\colon \exp\left(-\ \omega rep\colon.\sum_{m=1}^{p}(\theta m-\theta^{i}m^{1})^{2}\right)\right] \quad (1)$$

where j and k are the index for the chemotactic step and the index for the reproduction step, respectively.

2.3. Reproduction

The least healthy bacteria die and the remaining healthiest bacteria each split into two bacteria, which are placed in the same location, replacing the same number of unhealthy bacteria. This makes the population of bacteria constant.

2.4. Elimination and dispersal

It is possible that, in the local environment, the live population of bacteria changes either gradually (e.g., via consumption of nutrients) or suddenly due to some other influences. For each elimination-dispersal occurrence each bacterium is dispersed with a probability of ρe.d. In the proposed smart bacteria foraging algorithm (SBFA) it is assumed that bacterial foraging takes place in a homogeneous medium, so the probability is performed only for unhealthy bacteria. This gives a faster and a faster convergence than BFA.

As discussed in the behavior of animals in search of hunting, the communication facilities between them will lead to larger catches for the group. Given the mass movement of organisms (bacteria), this is possible. If we can determine the range of nutrients for bacteria, thus give allowing us the opportunity to reach larger feeds or hunts. Because of the GA, which is in the form of a set of chromosomes, simultaneously expands all genes to genetic processes [66]. This process can be used in the general movement of bacteria to reach a larger hunting area. So, in the proposed algorithm, first, by the general processes of a conventional GA, the bacteria enter the area likely to reach more extensive hunts. After that, the bacteria with the swimming (swim) and the wrong operator (tumble) move forward to find the smart nurture material (nurture). The steps of the proposed algorithm can be seen in Figure 1 [68].

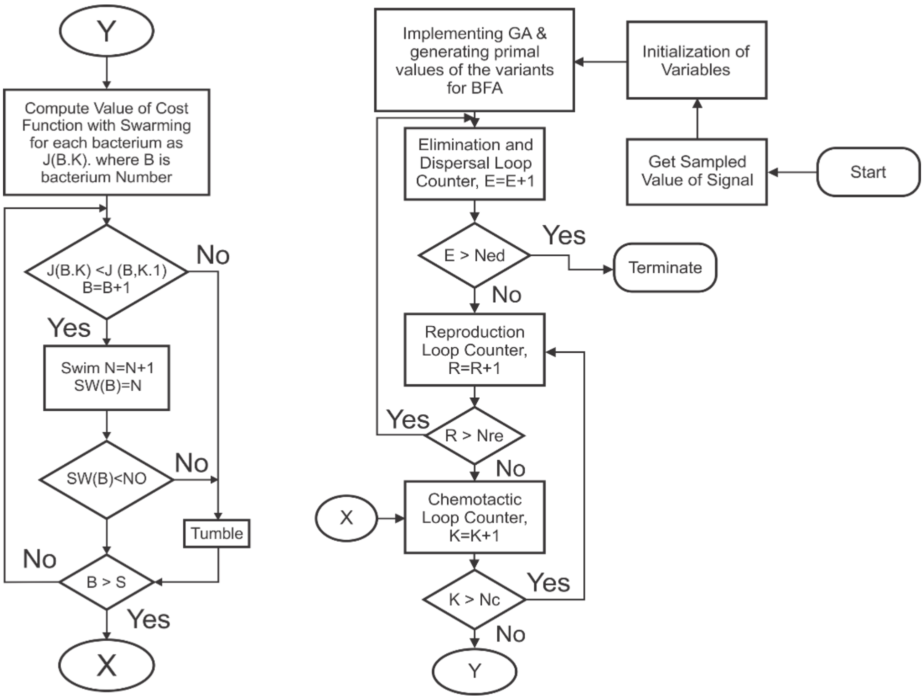

Figure 1. Operational schema of GA-BFA proposed hybrid algorithm

2.5. The initialization steps

Suppose that we want to find the minimum of $J\ (\theta), \theta\ \in\ \Re p$. The initialization steps are:
- Number of parameters (p) to be optimized;
- Number of bacteria (S) to be used for searching the total region;
- Swimming length Ns after tumbling of bacteria will be undertaken in a chemotactic loop;
- The number of iterations to be undertaken in a chemotactic loop Nc>Ns;

- Nr: the maximum number of reproductions to be undertaken;
- Ned: the maximum number of elimination and dispersal events to be imposed over the bacteria;
- ρe.d: the probability which the elimination and dispersal will continue;
- The location of each bacterium P (i, j, k) which is specified by P (i, j, k) {θ i (j, k, l) i=1, 2,..., S};
- The value of essential chemotactic step size " C(i) " for i=1, 2, …. S is assumed to be constant in our case for all of the bacteria to simplify the design strategy;
- To represent a tumble, a random direction unit length between (0,1) say $\phi\ (j)$ is generated. This will define the direction of movement after a tumble by using $\beta(i)$. The value of $\phi(j)$ is represented by:

$$\Delta(i) = \beta(i)\frac{\Delta(i)}{\sqrt{\Delta t(i)\Delta(i)}} \tag{2}$$

Where $\beta(i)$:{β m (i) | m=1,2,..., p} is 1 or -1 and $\Delta(i) \in R^p$, {Δ m (i) | m 1,2,..., p} is a random number on (0,1]. Also $\beta(i)$ at first is chosen randomly and then changes with attention to the cost function smartly [66].

2.1.5. The iterative algorithm for optimization

This section models the bacterial population chemotaxis, swarming, reproduction, elimination and dispersal (initially $j = k = l = 0$ and θ_i are chosen randomly).

Step 0) Initialization of variables Δ *(i)*, β 0 *(i)* and θ^i randomly. For *i*=1,2,..., *S,* calculate the cost function value for each bacterium using initial variables *(j=k=l=0)*, as follows. Compute the value of the cost function *J (i, j, k, l)* that: *Jsw (i, j, k, l) =J (i, j, k, l)+ Jcc* (θ^i *(j, k, l), P(j, k, l)*)

Step 1) Elimination-dispersal loop *l=l* + 1.

Step 2) Reproduction loop *k*=*k* + 1.

Step 3) Chemotaxis loop *j=j* + 1

a. For *i* =1,2,..., *S* calculate the cost function value for each bacterium *i* as follows. Compute the value of cost function *J (i, j, k, l)* let;

b. For *i*=1,2,..., *S,* take the tumbling/swimming decision. Tumble: Generate a random vector Δ(*i)* with each element. Move: let θ^i (j+1, *k, l)*=Γ= θ^i (j, *k, l)*+C(i)β(i)$\frac{\Delta(i)}{\sqrt{\Delta^t(i)\Delta(i)}}$. The fixed step size in the direction of tumble for bacterium is considered. Swim: 1) Let *N*=0; (counter for swim length); 2) While *N* < *Ns* (have not climbed down too long).

c. Go to the next bacterium *i*=*i* + 1 if *i* ≠ S(i.e., go to b) to process the next bacterium.

Step 4) If *j* < *Nc,* go to Step 3). In this case, continue chemotaxis since the life of the bacteria is not over.

Step 5) If *l* > *Ned,* the algorithm stops.

Step 6) Reproduction. For the given *k* and *l,* and for each *i*=1,2,..., *S,* let J^i*health*=min{ *J SW (i, j, k, l)*}, *j*∈ {1,... *Nc}* be the health of the bacterium (a measure of how much nutrients received over its lifetime and how successful it was at avoiding noxious substances). Sort bacteria in order of ascending cost *Jhealth* (higher cost means lower health).

Step 7) If *k* < *Nr,* go to 2. In this case, we have not reached the number of specified reproduction steps, so we start the next generation in the chemotactic loop.

Step 8) Elimination dispersal: after sorting bacterium in order of ascending cost Jhealth (higher cost means lower
health), for *i=Se.d, Se.d* +1,..., *S,* (*Se.d=n.S,*{*n* <1}) with probability ρ *e.d,* eliminate and disperse each bacterium (this keeps the number of bacteria in the population constant) to a random location on the optimization domain. After that, go to 1.

3. METHOD

In this study, an objective function based on the time domain and various operating conditions of the system is used to adjust the parameters of the PSS. A performance index is defined based on the system dynamics after creating a periodic disturbance in the system. It is organized for a wide range of operating conditions and to form the measure function of the problem. Since the operating condition of the power system is changing, the proposed objective function for a wide range of operating conditions is defined as [72]:

$$J = \mathrm{W1} \times \mathrm{J1} + \mathrm{W2} \times \mathrm{J2} \tag{3}$$

Where $W1$ and $W2$ are weighting coefficients and $J1$, and $J2$ are the two main parts of objective functions calculated by (4) and (5).

$$J1 = \sum_{I=1}^{Np} \int_0^{tsim} t(|W1 - W2| + |W1 - W3| + |W1 - W4|) + |W3 - W4|)\, dt \quad (4)$$

$$J2 = (500 \times \mathrm{OS})^2 + (8000 \times \mathrm{US})^2 + .0001 \times \mathrm{Ti}^2 \quad (5)$$

The $J1$ is based on local and inter-area frequency difference and the $J2$ is based on the overshoot, undershoot, and settling time of the oscillations. In (4), Tsim is the simulation time, and NP is the number of operating conditions for the optimization process, t is the time operator, and $W1$ to $W2$ are generators of angular velocity. Moreover, in (5), OV is overshoot, the US is undershooting, and Ti is settling time. The PSS design is formulated according to (6) as a constrained optimization problem with the following constraints:

$$\begin{aligned} &K^{min} \leq K \leq K^{max} \\ &T_1^{min} \leq T \leq T_1^{max} \\ &T_2^{min} \leq T_2 \leq T_2^{max} \\ &T_3^{min} \leq T_3 \leq T_3^{max} \\ &T_4^{min} \leq T_4 \leq T_4^{max} \end{aligned} \quad (6)$$

The objective is the determination of all PSS parameters, which are $k, T1, T2, T3,$ and $T4$ for all PSSs. The objective function is defined as:

$$OF = \sum_{Gn=1}^{m} \sum_{t=t0}^{tf} \Delta wGm(t).A.(t - t0).\Delta t \quad (7)$$

Where*:*
ΔwGm is the speed deviation of the generator n;
$t0$ is the time that the fault is cleared;
Δt is the speed signal sampling period and;
A is a weighting factor;
m is the number of PSSs or generators.

In (7) expresses the sum of the transient area under the speed response of each generator for a specific disturbance (e.g., a three-phase short circuit). However, this tuning criterion increases the probability of trapping the optimization method in local minima. To explain this matter, suppose two typical generator responses to a specific disturbance are shown. The two responses are separated by thick and narrow lines and are entitled "response 1" and "response 2," respectively. Response 1 and response 2 have a transient area under the curve of 0.25 and 0.15, respectively. Despite the fact that the objective function of response 2 (the narrow line) is less than response 1, it is not an acceptable solution, and this represents the shortcoming of previous objective functions. Indeed, response 2 is a local minimum, and the algorithm must have the ability to escape from such local minimums. In the next section, where the power grid and the results from PSS types are expressed, one can see the quality of each type of CPSS and optimal CPSS (OCPSS) stabilizers. The CPSS has more damping of fluctuations and a lower transient response than the OCPSS. In addition, the optimization implementation process is shown in Figure 2. As shown in the figure, the proposed hybrid performance performed better than the conventional GA method, pushing the standard objective function to a more appropriate point in a given situation.

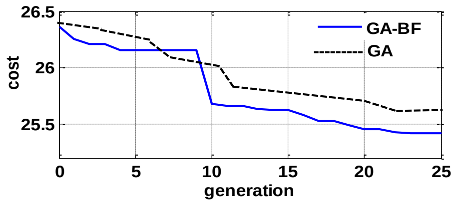

Figure 2. Diagram of implementation of optimization algorithms (GA and GA_BFA)

Commonly used PSSs, are generally based on filter speed error. And compensated generators are built. You can see a linear model of it in Figure 3, which consists of an amplifier, a low-pass filter and two pre-phase-post-phase compensators and a limiter [68]. But as stated in the first part, proper adjustment of the coefficients of this stabilizer due to the nonlinear and complex nature of the system, leads to difficulties. For this reason, using bio-evolutionary optimization algorithms here, we try to adjust these coefficients. Also, the proposed design of a classical stabilizer used for optimization can be seen in Figure 4. In this structure, a compensator is used in addition to the conventional initial design of Figure 3. The type of these compensators is determined by the optimization algorithm with appropriate adjustment of their coefficients. This third compensator can reduce the quality of system performance by changing the working point and improve the results. In optimizing CPSS, in this paper, a GA_BFA optimization hybrid algorithm is used. The objective is the optimal determination of all PSS parameters so that the network has maximum damped response during all considered contingencies. A typical block diagram of a PSS is shown in Figure 4. It consists of an amplifier block of constant gain k, a block having a washout time Tw, and two lead-lag compensators with time constant $T1$ to $T4$. The washout block is provided to eliminate the steady-state bias in the output of PSS. Tw is usually pre-specified. Thus, this parameter is not considered a control variable, and it has been set to 10 in all PSSs [70].

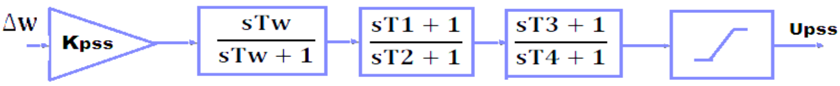

Figure 3. Block diagram of CPSS

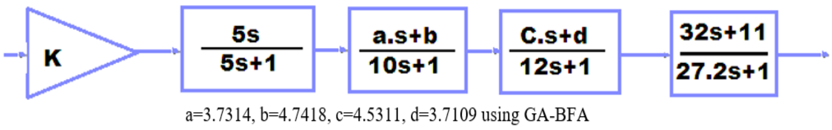

Figure 4. Block diagram of optimized conventional stabilizer (OCPSS)

4. RESULTS AND DISCUSSION

Here, an IEEE standard four-machine network is selected to test the stabilizers mentioned above, and the types of stabilizers in question are applied to the system machines according to Figures 5 and 6 [63], [66]. To demonstrate the effectiveness of these optimization methods for improving power system performance, the proposed technique was tested on a standard two-area, four-machine power system. This system contains six buses, four generators, and two identical areas connected by a relatively weak tie-line between buses 3 and 4. Each area has two generators with the same power output. A total of two loads are available on buses 3 and 4. Two shunt capacitors are also connected to buses 3 and 4. The single-line diagram of the system is presented in Figure 6. The complete data for this system is found in Kunder. For testing, a three-phase fault occurs in line 3 in the first second, which is eliminated after 0.2 seconds with the cut-off of the line. Here is the machine number 1 that tested the various stabilizers discussed on it, and the other machines have conventional fixed stabilizers. Simulation results are carried out using a 3-phase fault in the middle of lines 3-4. This fault occurs at second 1 and will be cleared with a tripping tie-line between two areas after 1/60 second. As an example, CPSS coefficients and optimization amounts by using the BFA and GA-BFA algorithms for machine one is shown in Table 1. The diagram related to CPSS in machine 1, along with Figure 7(a) the changes of rotor speed-G1, Figure 7(b) rotor speed-G1, Figure 7(c) rotor angle relative to machine 4-G1,2,3, Figure 7(d) accelerating torque, and Figure 7(e) the real power transferred from bus 3 to bus 4.

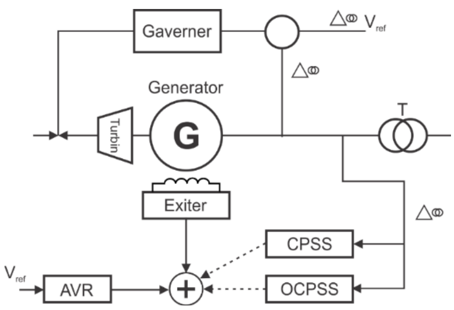

Figure 5. Graphical view of a generator with the PSS and automatic voltage regulator (AVR) system

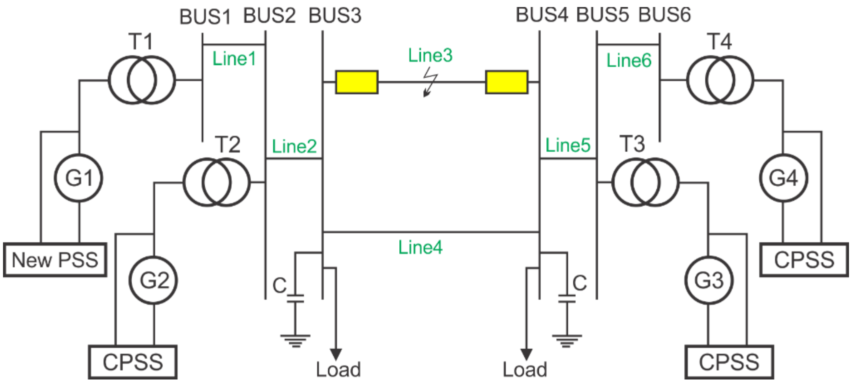

Figure 6. The configuration of the studied IEEE standard four-machine power system

Table 1. Conventional, BFA, and GA-BFA based PSS parameters for machine 1

Technique/coefficients	Conventional	BFA	GA-BFA
T1	0.05	0.70	3.50
T2	0.02	10.00	10.00
T3	4.50	1.22	0.52
T4	5.00	12.00	12.00

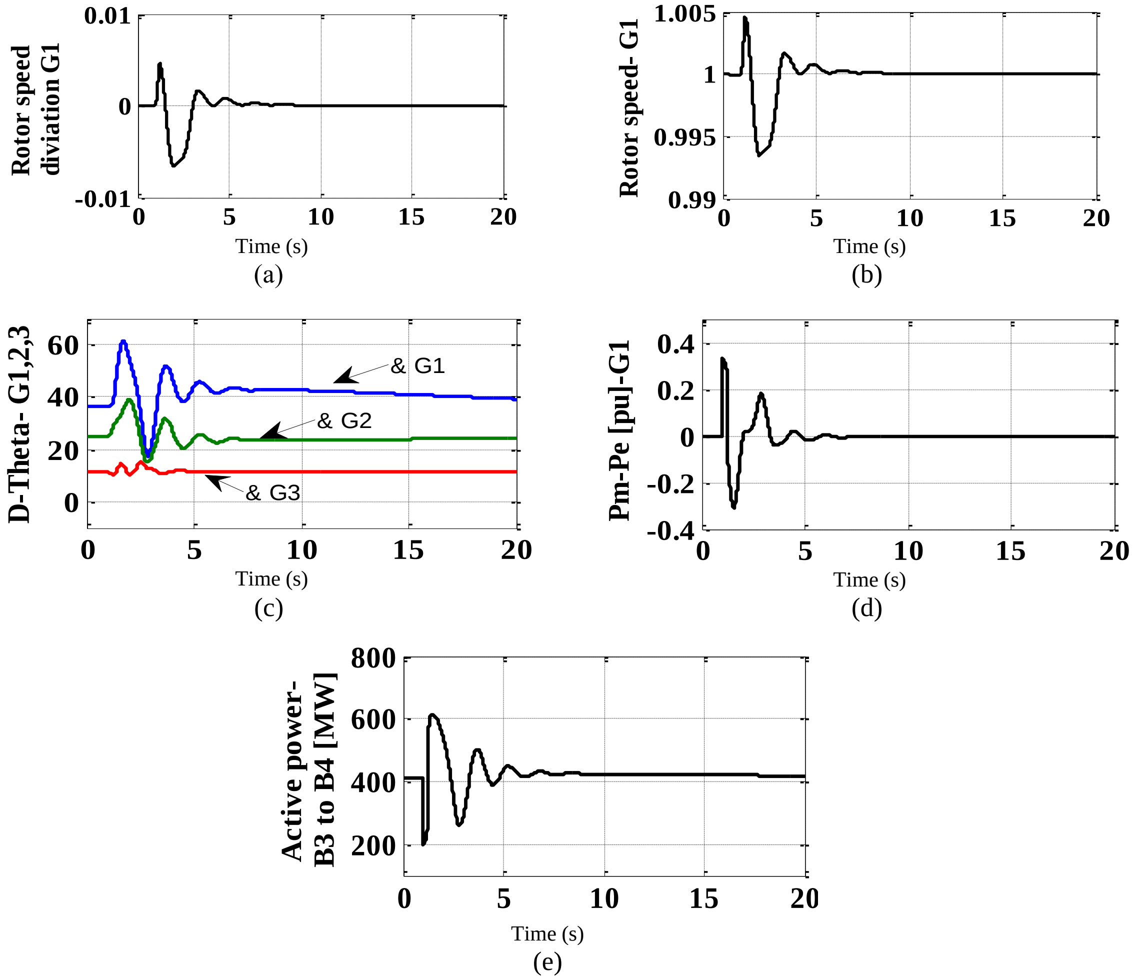

Figure 7.Diagram of CPSS in machine 1 (a) rotor speed variation-G_1, (b) rotor speed-G_1, (c) rotor angle relative to machine 4-$G_{1,2,3}$, (d) accelerator torque, and (e) transfer active power from bus 3 to bus 4

The diagram related to the use of OCPSS, in machine 1 along with Figure 8(a) the changes in rotor speed-G1, Figure 8(b) rotor speed-G1, Figure 8(c) rotor angle with respect to machine 4-G1,2,3, Figure 8(d) accelerating torque and Figure 8(e) the real power transferred from bus 3 to bus 4 (all generators are equipped with BFA-PSS). After applying a short circuit in line 3, the system oscillates after a cycle of about 4 seconds, but then the signal error under control moves to a permanent zero state. The reason for this can be explained by the existence of an integral system in this design. In the presence of the error integral, the system will move to the permanent zero error state. In parts D of Figures 7 and 8, the difference between mechanical and electrical power (Pm and Pe) is plotted; in the proposed design, the system reaches damping after about one oscillation in 4 seconds, but in the conventional CPSS design, this damping is achieved after about three oscillations in 6 seconds. As can be seen, the performance quality observed as a result of using OCPSS to damp frequency fluctuations is also obtained in these diagrams. One of the PSS's most important goals is to track mechanical power by electrical power. Finally, we can see the overall improvement in various dimensions of system performance, which indicates the superiority of the proposed design. This performance improvement has also had a positive effect on other parts of the system. Figures 7 and 8 of part C show the damping speed of the load angular of the systems. As a result, the network has better overall performance with the proposed stabilizer.

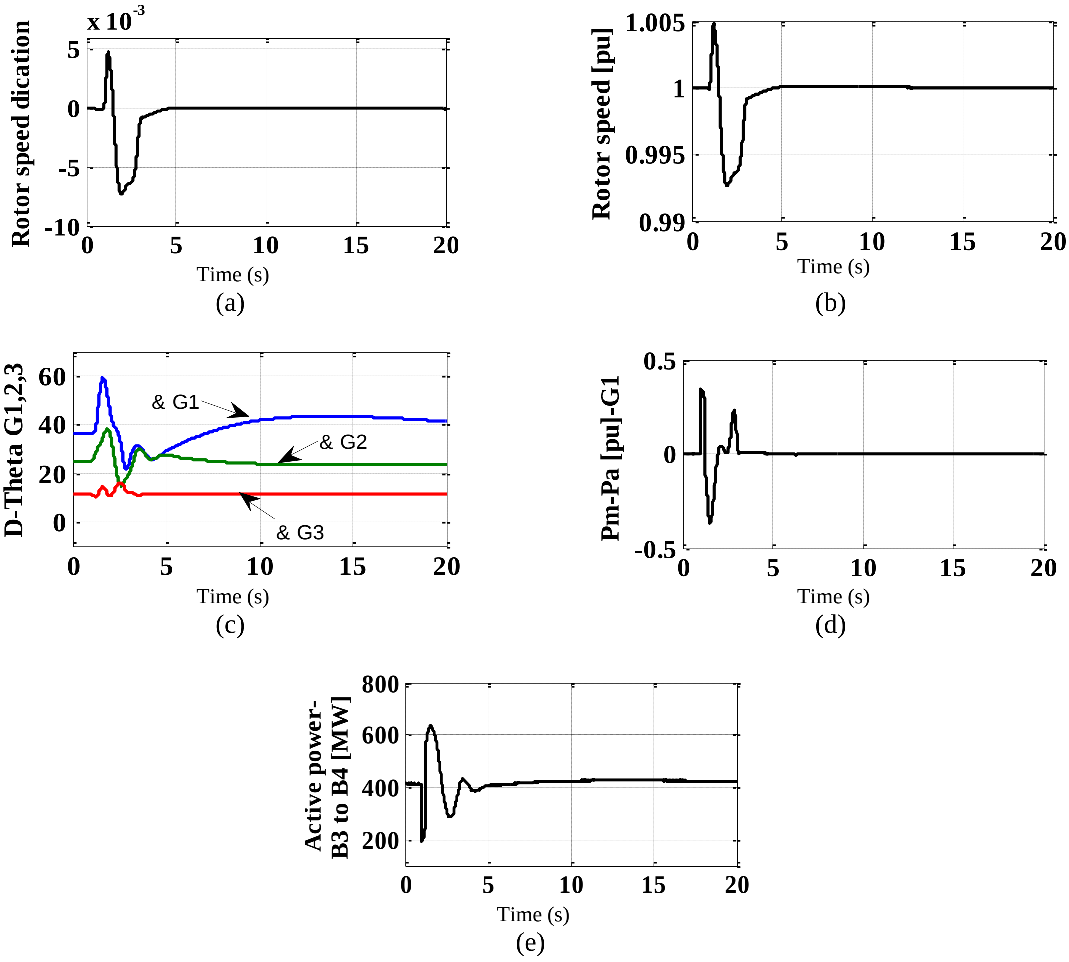

Figure 8.Diagram of OCPSS in machine 1 (a) rotor speed variation-G_1, (b) rotor speed-G1, (c) rotor angle relative to machine 4-$G_{1,2,3}$, (d) accelerator torque, and (e) transfer active power between buses 3 and 4 (all generators are equipped with BFA-PSS)

5. CONCLUSION

In this research, power systems are inherently nonlinear and variable systems, which in order to control them and especially their stability process. Also, in this study, with the suggestion of stabilizer OCPSS, the advantages of conventional systems CPSS can be exploited through advanced optimization systems. Notably, conventional systems, due to their simple structure, have been advantageous such as easy implementation and low cost over nonlinear and intelligent systems. To improve the stable performance of the power system, a suitable optimization system was used that brought the user closer to the desired goals. It was also observed that, with proper adjustment of a stabilizer, its positive effects could be felt on other network parts. This design can be well used industrially and even in the reconstructing of old and conventional systems, with such a structure to improve performance at a lower cost. This algorithm considers both social, and individual intelligence of bacteria for finding a better nutrition path without any deflection from bacteria group movement. Simulation results of conventional, GA-BFA and BAF-based PSS in a two-area four-machine power system showed the effectiveness of the proposed method. Some suggestions for continuing research in this regard can be listed: improve power system stability using FACTS devices based on fuzzy controllers, indirect adaptive controllers, model predictive control (MPC) and nonlinear controllers. Implement the proposed controller on DSP boards. Implement the proposed controller on FPGA boards.

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