Journal of Engineering and Applied Sciences 9 (6): 217-223, 2014
ISSN: 1816-949X

Optimal Tuning of Pid Power System Stabilizer for Multi Machine Power System Using Bacterial Foraging Algorithm (BFA)

[1]K. Abdul Hameed and [2]S. Palani
[1]Anna University, Chennai,
[2]Sudharsan Engineering College, Sathyamangalam, Tamil Nadu, India

Abstract: This study presents a novel Bacterial Foraging Algorithm (BFA) to tune optimal gains of a Proportional Integral Derivative (PID) type multiple stabilizers for multi machine power system. The problem of robustly tuning of PID based multiple stabilizer design is formulated, as an optimization problem according to the time domain-based objective function which is solved by Bacterial Foraging Algorithm (BFA) that has a strong ability to find the most optimistic results. To demonstrate the effectiveness and robustness of the proposed stabilizers, the design process takes a wide range of operating conditions and system configuration into account. The effectiveness of the proposed stabilizer is demonstrated through non-linear simulation studies and performance indices on a 4 machine 2 area power system in comparison with the Conventional Power System Stabilizers (CPSS) and Particle Swarm Optimization (PSO) based optimized PID type stabilizers (PSOPSS). The results of these studies show that the proposed BFA based optimized PID type stabilizers have an excellent capability in damping power system inter-area oscillations and enhance greatly the dynamic stability of the power system for a wide range of operating conditions. The results obtained using the proposed method is much superior than those obtained by CPSS and PSOPSS based tuned stabilizers in terms of accuracy, convergence and computational effort.

Key words: Bacterial foraging algorithm, power system stabilizer, power system stability, PID controller, India

INTRODUCTION

Power systems are highly non-linear and exhibit low frequency oscillations due to poor damping caused by the high-gain, fast-acting Automatic Voltage Regulator (AVR) employed in the excitation system. The power system utilities employ Power System Stabilizers (PSSs) to introduce supplementary stabilizing signals into the excitation system to increase the damping of the low frequency oscillations. Among various types of PSSs, the fixed-structure lag-lead type (CPSS) is preferred by the utilities due to its operational simplicity and ease of tuning PSS parameters. However, the robustness of these PSS under changing conditions is a major concern. The concept of PSSs and their tuning procedures were well explained in literature. A well-tuned lag-lead type Conventional PSS can effectively improve dynamic stability. Many approaches have been proposed to tune PSSs, such as the sensitivity approach (Fleming *et al*., 1981), pole placement technique (Abido and Abdel-Magid, 2002) and the damping torque approach (Kundur *et al*., 1989). Global optimization technique like Genetic Algorithm (GA) (Abdel-Magid *et al*., 1999), Particle Swarm Optimization (PSO) (Abido and Abdel-Magid, 2002), tabu search (Rafiee and Meyabadi, 2012) and simulated annealing (SA) (Abido, 2000) are attracting the attention in the field of PSS parameter optimization in recent times. But when the system has a highly epistatic objective function (i.e., where the parameters being optimized are highly correlated) and number of parameters to be optimized are large, GA has been reported to exhibit degraded efficiency (Hameed and Palani, 2013a). Bacterial foraging algorithm has been proposed and introduced as a new evolutionary technique by Passino (2002) and Hameed and Palani (2013b). To overcome the drawbacks of conventional methods for PSS design, a new optimization scheme known as Bacterial Foraging (BF) is used for the PSS parameter design (Hameed and Palani, 2013a). This algorithm (BFA) appeared, as a promising one for handling the optimization problems (Passino, 2002). It is a computational intelligence based technique that is not largely affected by the size and non-linearity of the problem and can converge to the optimal solution in many cases where many analytical methods fail to converge. Considering the strength of this algorithm, it is employed in the present reseach for the optimal tuning the parameters of the PSS.

Corresponding Author: S. Palani, Sudharsan Engineering College, Sathyamangalam, Tamil Nadu, India

In this study, a new/improved BFA-based optimal determination of PID-PSS parameters is presented which overcomes the shortcomings of previous research. In order to design, a robust PSS which guarantees stability of system in a wide range of operating conditions, the objective function is defined such that the resultant time response is restricted to lie within specific bounds, as well as limiting the amount of overshooting of power system response when subjected to disturbances. The performance of the BFAPSS is compared with those obtained with other techniques, such as conventional and Particle Swarm Optimization (PSO) by plotting the time response curves for the faults.

MATERIALS AND METHODS

Power system model studied: A 4 machine, 2 area study system, shown in Fig. 1 is considered for the damping controller design. Each area consists of 2 generator units. The rating of each generator is 900 MVA and 20 kV. Each of the units is connected through transformers to the 230 kV transmission line. There is a power transfer of 400 MW from area 1-2. The detailed bus data, line data and the dynamic characteristics for the machines, exciters and loads are given by Shayeghi *et al.* (2011). The loads are modeled, as constant impedances. For the power system stability analysis a reasonably accurate mathematical model which takes into account the non-linear ties in the system is highly essential. The two-axis model (fourth order) given by Hameed and Palani, 2013a is used for the time domain simulations study for each machine. The loads are modeled as constant impedances. A first order model of a static type automatic voltage regulator is used. Non-linear dynamic equations of the each machine can be summarized as follows:

$$\dot{\delta}_i = \omega_b(\omega_i - 1) \tag{1}$$

$$\dot{\omega}_i = \frac{1}{M_i}\left(P_{mi} - P_{ei} - D(\omega_i - 1)\right) \tag{2}$$

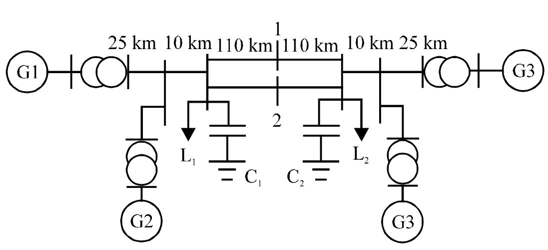

Fig. 1: Single line diagram of 2 area system

$$\dot{E}'_{qi} = \frac{1}{T'_{doi}}\left(E_{fdi}(x_{di} - x'_{di})i_{di} - E'_{qi}\right) \tag{3}$$

$$\dot{E}_{fdi} = \frac{1}{T_{Ai}}\left(K_{Ai}(\nu_{refi} - \nu_i + u_1) - E_{fdi}\right) \tag{4}$$

$$T_{ei} = E'_{qi}\, i_{qi} - (x_{qi} - x'_{di})i_{di}\, i_{qi} \tag{5}$$

PSS structure: The operating function of a PID type PSS is to produce a proper torque on the rotor of the machine involved in such a way that the phase lag between the exciter input and the machine electrical torque is compensated. The supplementary stabilizing signal considered is one proportional to speed. A widely used speed based PID is considered throughout the study (Hameed and Palani, 2013a). The transfer function of the ith PID type stabilizer is given by:

$$U_i = \frac{T_w s}{1 + T_w s}.\left(K_P \frac{K_I}{s} + \frac{K_D s}{1 + T_D s}\right)\Delta\omega_i(s) \tag{6}$$

Where:

TD<<1	=	It is considered as KD/100
$\Delta\omega_i$	=	The speed deviation of the ith generator
U_i	=	The output signal fed, as a supplementary input signal to the regulator of the excitation system

This type of PSS consists of a washout filter and a PID compensator. The washout filter which really is a high pass filter is regarded, as to reset the steady-state offset in the output of the stabilizer. The value of the time constant T_w is usually not critical and it can range from 1-20 sec.

This study attempts to optimize the parameters (Kp, Ki, Kd) of PID-PSS via a Bacterial foraging algorithm is inspired by an activity called chemotaxis exhibited by bacterial foraging behaviours.

Particle Swarm Optimization (PSO): Particle Swarm Optimization (PSO) is a population based stochastic optimization technique developed by Eberhart and Kennedy (Soliman *et al.*, 2008). It shares many similarities with evolutionary computation techniques, such as Genetic Algorithms (GA). The system is initialized with a population of random particles where each particle is a candidate solution. The particles fly through the problem space by following the current optimum particles and searches for optima by updating their positions. However, unlike GA, PSO has no evolution operators, such as crossover and mutation. The advantages of PSO over GA are the ease of programming and fast convergence (Fogel, 1995; Seifossadat *et al*., 2007). In the PSO algorithm, each particle updates its velocity and position by the following relationships:

$$v_i^{k+1} = wV_i^k + c_1 rand_1 \left(pbest_i - s_i^k\right) + c_2 rand_2 \left(gbest_i - s_i^k\right) \quad (7)$$

$$s_i^{k+1} = s_i^k + v_i^{k+1} \quad (8)$$

Where:

c_1 and c_2	=	The cognition and social parameters
$rand_1$ and $rand_2$	=	The constant numbers in the range of Kundur *et al*. (1989)
w	=	The inertia weight
V_i	=	The velocity of the ith particle
s_i	=	Its position
$pbest_i$ and $gbest_i$	=	Local best and global best positions

The velocity of particle in Eq. 7 depends on its previous velocity, its own thinking and social psychological adaptation of the population. The PSO algorithm starts with random initialization of population and velocity. The search for the optimum solution is continued unless one of the stopping criteria is reached. The stopping criteria are either the maximum iterations are reached or there is no further improvement in the optimal solution. The values of parameters for PSO used in this study are as follows:

No. of particles 30; No. of swarms 12 (Kp_i, Ki_i, Kd_i); No. of iteration = 500; Maximum particle velocity (upper-lower bound)/No. iteration = 0.05; c1, c2 =2, 2; wmax, wmin = 0.9, 0.4.

Bacterial Foraging Algortihm (BFA): Bacterial foraging algorithm (Passino, 2002; Shayeghi *et al*., 2011) is inspired by an activity called chemotaxis exhibited by bacterial foraging behaviours. Motile bacteria such as *E. coli* and salmonella propel themselves by rotation of the flagella. To move forward, the flagella rotates counter clockwise and the organism swims or runs while a clockwise rotation of the flagellum causes the bacterium to randomly tumble itself in a new direction and swim again alternation between swim and tumble enables the bacterium to search for nutrients in random directions. Swimming is more frequent as the bacterium approaches a nutrient gradient. Tumbling, hence direction changes is more frequent as the bacterium moves away from some food to search for more. Basically, bacterial chemotaxis is a complex combination of swimming and tumbling that keeps bacteria in places of higher concentrations of nutrients. The foraging strategy of *Escherichia coli* bacteria present in human intestine can be explained by 3 processes; namely chemotaxis, reproduction and elimination dispersal.

In chemotaxis, a unit walk with random direction represents a tumble and a unit walk with the same direction in the last step indicates a run. C (i) is called the run length unit parameter is the chemo tactic step size during each run or tumble. With the activity of run or tumble at each step of the chemotaxis process, a step fitness will be evaluated. In the reproduction step, all bacteria are stored in reverse order according to the health status. Here, only the 1st half of the population survives and a surviving bacterium splits into 2 identical ones which are then placed in the same locations. Thus, the population of bacteria keeps constant. It is possible that in the local environment, the life of a population of bacteria changes either gradually by consumption of nutrients or suddenly due to some other influence. Events can kill or disperse all the bacteria in a region. They have the effect of possibly destroying the chemotactic progress but in contrast, they also assist it, since dispersal may place bacteria near good food sources. Elimination and dispersal helps in reducing the behavior of stagnation (i.e., being trapped in a premature solution point or local optima). The flow chart of the iterative algorithm is shown in Fig. 2. The bacteria with large run length unit C (i) have the exploring ability and stay for a while in several domains containing local optima. It can also escape from the local optima to enter the domain with global optima. On the other hand, a bacterium with small run length unit C (i) is attracted in to the domain with local optima and exploited this local minimum for its whole life

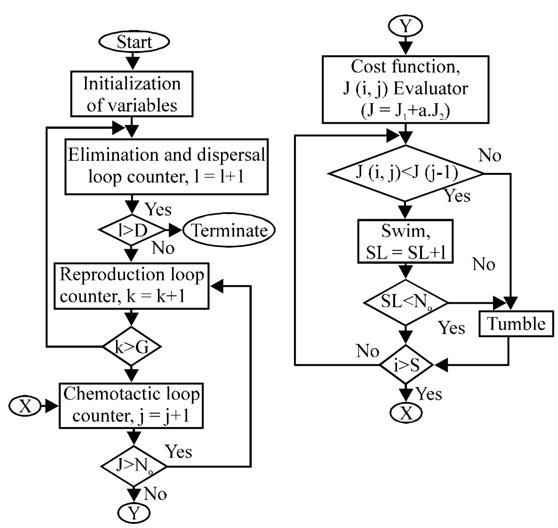

Fig. 2: Flow chart of bacterial foraging algorithm

cycle. It is therefore necessary to choose the value of C (i) with larger value for faster convergence. In this algorithm, cost function value is taken as objective function and the bacterium having minimum cost Function (F) is retained for the next generation. For swarming, the distances of all the bacteria in a new chemotactic stage are evaluated from the global optimum bacterium till that point. To speed up the convergence, a simple heuristic rule to update one of the Coefficients (C) of BFA algorithm is formulated.

BFA based PSS: This study describes how the BFA algorithm is employed to tune the PID type PSS parameters for the 2 area multi-machine power system which is shown in Fig. 1. Just like any other optimization problem, an objective function (performance index) needs to be formulated to determine optimal parameters of multiple PSSs. The optimal values of these parameters depend upon the cost function used for optimization. Each individual in the initial harmony has an associated Performance Index (PI) value. The performance indices (Shayeghi *et al*., 2011) used here are of the following form: The Integral of the Square of the Error criterion (ISE) which is given by:

$$ISE = 10^4 X \int_0^{tsim} \left(\Delta\omega_{12}^2 + \Delta\omega_{13}^2 + \Delta\omega_{14}^2 + \Delta\omega_{34}^2\right) \quad (9)$$

The Integral of Time-multiplied Absolute value of the Error criterion (ITAE). The criterion penalizes long-duration transients and is much more selective than the ISE. A system designed by use of this criterion exhibits small overshoot and well damped oscillations. It is given by:

$$ITAE = 10^4 \int_0^{tsim} \left(|\Delta\omega_{12}| + |\Delta\omega_{13}| + |\Delta\omega_{14}| + |\Delta\omega_{34}|\right) \quad (10)$$

IAE integrates the absolute error over time. It does not add weight to any of the errors in a systems response. It tends to produce slower response than ISE optimal systems but usually with less sustained oscillations. It is given by:

Table 1: Operating conditions

Conditions	OP1	OP2	OP3
P1	0.7778	0.5556	0.9911
Q1	0.2056	0.2056	0.1722
P2	-0.1084	0.5556	0.6283
Q2	0.8020	0.2611	0.5836
P3	0.8883	0.5556	1.1110
Q3	0.2244	0.2244	0.2222

$$IAE = 10^4 \int_0^{tsim} \left(|\Delta\omega_{12}| + |\Delta\omega_{13}| + |\Delta\omega_{14}| + |\Delta\omega_{34}|\right) \quad (11)$$

$$F = \frac{1}{(1 + \Delta\omega p) + (1 + ts)} \quad (12)$$

Where, $\Delta\omega p$ and ts are mean overshoot, mean settling time of 4 relative speed deviations. The optimal tuning of the PSS parameters is carried out by evaluating the fitness Functions (F), as given in Eq. 9-12 for the operating conditions as given in Table 1. A 6-cycle 3 phase fault is applied at the middle of one of the transmission line between bus-7 and 8. The fault is cleared by permanent tripping of the faulted line. In this study, the BFA module works offline. For each PSS, the optimal setting of 4 parameters is determined by the BFA, i.e., 12 parameters are to be optimized.

RESULTS AND DISCUSSION

The effectiveness and robustness of the performance of the proposed PID type stabilizer under transient conditions is verified by applying a 3 phase fault of 100 ms duration at the middle of one of the transmission lines between bus-7 and 8. The fault is cleared by permanent tripping of the faulted line. To evaluate the performance of the proposed stabilizer design approach the response of the proposed PSS are compared with the response of the PSO and CPSS. The inter-area and local mode of oscillations with the above stabilizers for different operating conditions (Moradi *et al*., 2012) as given in Table 1 is shown in Fig. 3-5, respectively. The performance of the BFA based optimized multiple PID type stabilizer is quite prominent in comparison with the other PSSs and the overshoots and settling time are significantly improved with the proposed stabilizer.

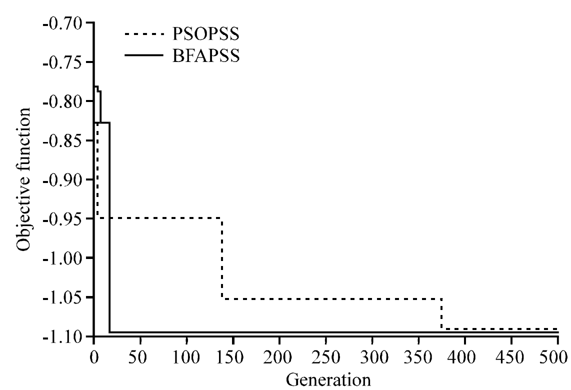

Fig. 3: Convergence comparison between PSO and BFA

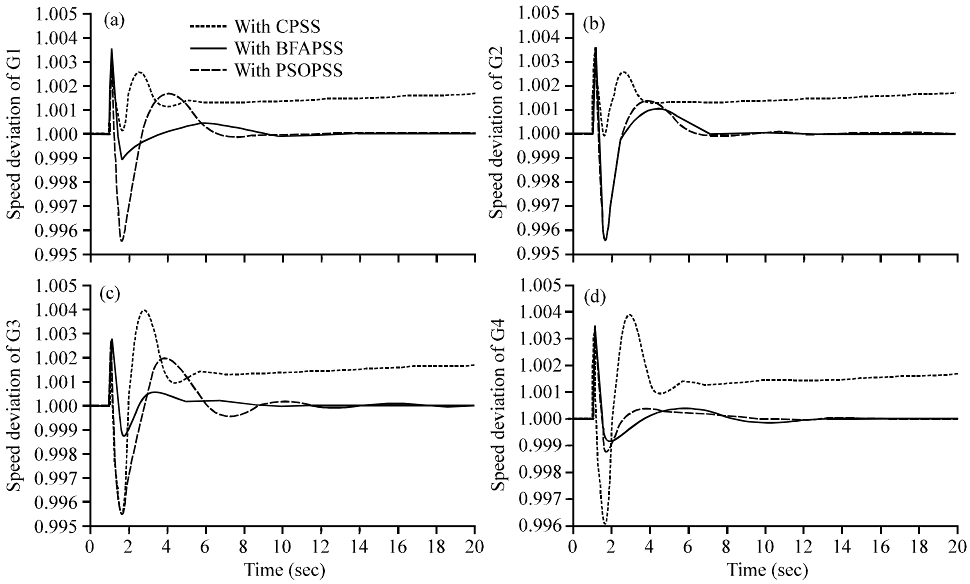

Fig. 4: Inter-area and local mode oscillations for operating condition 1

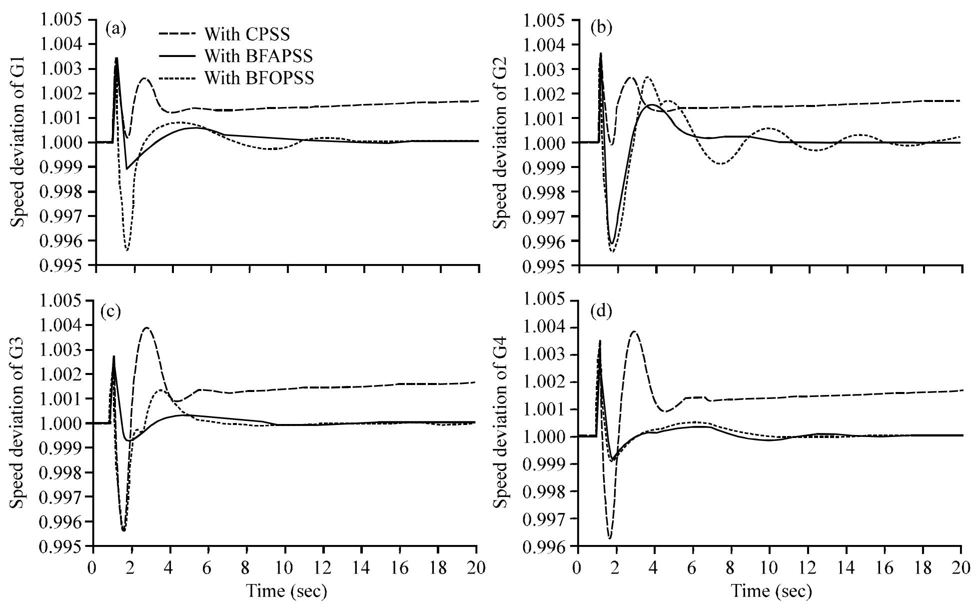

Fig. 5: Inter-area and local mode oscillations for operating condition 2

Table 2: Performance indices under different operating conditions

Algorithm	OP1 (ITAE)	OP2 (IAE)	OP3 (IAE)
BFA	16.533	12.432	1.2532
	26.432	25.561	2.3459
	16.437	16.855	1.5671
PSO	20.562	11.349	2.2098
	22.560	9.459	3.4633
	17.674	10.354	1.7733

Figure 3 illustrates the convergence of the objective Function (F) with Particle Swarm Optimization (PSO) and BFA. From the convergence characteristics, it is clear that BFA offers superior performance than PSO. From Fig. 4-6 and Table 2-4, it is observed that the performance of the PSS designed using BFA is far superior compared to the PSS designed using Particle Swarm Optimization (PSO). In addition, Table 2-4 reveals that by using the proposed BFA technique, the speed deviations of all the machines are greatly reduced has small overshoot and settling time.

It is merit mentioning that the lower the value of these indices is the better the system response in terms of

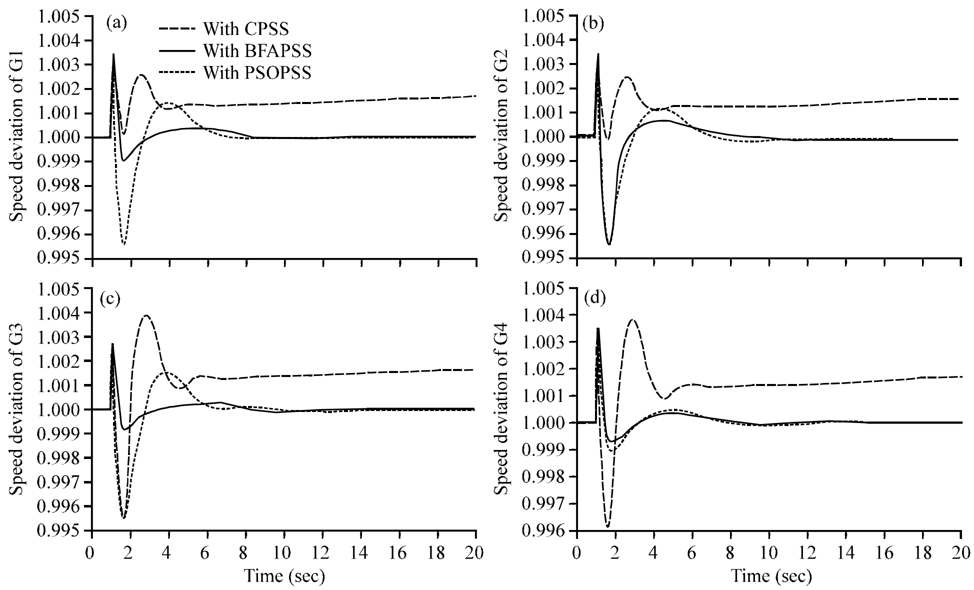

Fig. 6: Inter-area and local mode oscillations for operating condition 3

Table 3: Optimal parameters of PID PSS under different operating conditions

Operating conditions	BFAPSS	PSOPSS
OP1	Kp1 = 56.7231	Kp1 = 43.49898
	Kp2 = 70.5697	Kp2 = 85.88287
	Kp3 = 69.9105	Kp3 = 52.27263
	Kp4 = 59.9096	Kp4 = 49.85963
	Ki1 = 27.9889	Ki1 = 71.75443
	Ki2 = 28.0689	Ki2 = 36.08533
	Ki3 = 15.6781	Ki3 = 9.040921
	Ki4 = 34.4917	Ki4 = 67.06363
	Kd1 = 45.7238	Kd1 = 133.8218
	Kd2 = 34.4192	Kd2 = 114.9234
	Kd3 = 56.5521	Kd3 = 23.37183
	Kd4 = 46.525	Kd4 = 92.52788
OP2	Kp1 = 43.3946	Kp1 = 120.7615
	Kp2 = 29.55834	Kp2 = 27.80057
	Kp3 = 104.323	Kp3 = 15.54715
	Kp4 = 28.36145	Kp4 = 96.80758
	Ki1 = 79.63496	Ki1 = 75.88975
	Ki2 = 7.396793	Ki2 = 44.43751
	Ki3 = 15.6781	Ki3 = 64.1663
	Ki4 = 5.43875	Kd4 = 92.11856
	Kd1 = 125.742	Kd1 =114.7058
	Kd2 = 57.1332	Kd2 = 73.028
	Kd3 = 35.91021	Kd3 = 96.2953
	Kd4 = 29.71308	Kd4 = 44.36207
OP3	Kp1 = 120.7615	Kp1 = 43.43277
	Kp2 = 27.80057	Kp2 = 29.55834
	Kp3 = 104.3237	Kp3 = 99.83914
	Kp4 = 96.8075	Kp4 = 25.71863
	Ki1 = 75.88975	Ki1 = 79.18229
	Ki2 = 44.43751	Ki2 = 23.77429
	Ki3 = 64.1663	Ki3 = 5.636135
	Ki4 = 44.36207	Ki4 = 5.363027
	Kd1 = 114.7058	Kd1 = 128.8646
	Kd2 = 73.028	Kd2 = 57.63613
	Kd3 = 96.2983	Kd3 = 37.50805
	Kd4 = 92.11856	Kd4 = 30.03774

the time-domain characteristics. Numerical results of performance robustness for all system loading cases are

Table 4: Settling time (ts) maximum peak overshoots (ωp) comparison

Operating conditions	Generator	PSOPSS ts (sec)	PSOPSS ωp	BFAPSS ts (sec)	BFAPSS ωp
OP1	G1	8.4	1.0027×10^{-4}	2.7	1.0036×10^{-4}
	G2	11.3	1.0026×10^{-4}	9.5	1.0020×10^{-4}
	G3	6.3	1.0027×10^{-4}	12.5	1.0020×10^{-4}
	G4	13.3	1.0037×10^{-4}	12.0	1.0028×10^{-4}
OP2	G1	14.2	1.0033×10^{-4}	13.7	1.0023×10^{-4}
	G2	18.4	1.0027×10^{-4}	10.2	1.0022×10^{-4}
	G3	10.2	1.0027×10^{-4}	11.4	1.0022×10^{-4}
	G4	15.7	1.0036×10^{-4}	14.3	1.0028×10^{-4}
OP3	G1	10.7	1.0020×10^{-4}	8.4	1.0010×10^{-4}
	G2	11.5	1.0020×10^{-4}	10.2	1.0027×10^{-4}
	G3	11.1	1.0027×10^{-4}	6.1	1.0022×10^{-4}
	G4	10.3	1.0036×10^{-4}	12.3	1.0028×10^{-4}

shown in Table 2 with 3 PID type stabilizers by applying a 3 phase fault of 100 ms duration at the middle of one of the transmission lines between bus-7 and 8. From Table 2, it is observed that the using the proposed BFA algorithm, the speed deviations of all machines are greatly reduced with small overshoots, undershoots and shorter settling time. Further, it achieves good robust performance compared to that of stabilizers designed using the PSO and conventional methods.

CONCLUSION

In this study, novel/improved Bacterial Foraging Algorithm (BFA) has been successfully applied to the robust design of multiple PID type stabilizers to improve damping of the low frequency oscillation in the multi machine power system. The design problem of the robustly selecting stabilizer parameters is converted into an optimization problem according to time domain-based objective function over a wide range of operating conditions that is solved by the BFA technique. It has stronger global search ability and more robust than PSO and other heuristic methods. The effectiveness of the proposed strategy was tested on a 2 area 4 machine power system under different operating conditions. The non-linear time domain simulation results demonstrate the effectiveness of the proposed PID type stabilizers and their ability to provide good damping of low frequency oscillations. The system performance characteristics in terms of ITAE, IAE, ISE and F indices reveal that the proposed BFA algorithm is superior that of the PSO and others in terms of accuracy and computational effort.

REFERENCES

Abdel-Magid, Y.L., M.A. Abido, S. Al-Baiyat and A.H. Mantawy, 1999. Simultaneous stabilization of multimachine power systems via genetic algorithms. IEEE Trans. Power Syst., 14: 1428-1439.

Abido, M.A., 2000. Robust design of multimachine power system stabilizers using simulated annealing. IEEE Trans. Energy Conver., 15: 297-304.

Abido, M.A. and Y.L. Abdel-Magid, 2002. Eigenvalue assignments in multimachine power systems using tabu search algorithm. Comput. Electr. Eng., 28: 527-545.

Fleming, R.J., M.A. Mohan and K. Parvatisam, 1981. Selection of parameters of stabilizers in multimachine power systems. IEEE Trans. Power Apparatus Syst., PAS-100: 2329-2333.

Fogel, D.B., 1995. Evolutionary Computation: Toward a New Philosophy of Machine Intelligence. IEEE Press, New York, USA., ISBN-13: 9780780310384, Pages: 272.

Hameed, K.A. and S. Palani, 2013a. Design of robust PID controller for power system stabilization using bacterial foraging algorithm. Nonlinear Dynam. Syst. Theor., 13: 412-424.

Hameed, K.A. and S. Palani, 2013b. Robust design of power system stabilizer using bacterial foraging algorithm. Arch. Electr. Eng., 62: 141-152.

Kundur, P., M. Klein, G.J. Rogers and M.S. Zywno, 1989. Application of power system stabilizers for enhancement of overall system stability. IEEE Trans. Power Syst., 4: 614-626.

Moradi, M.H., S.M. Moosavi and A.R. Reisi, 2012. Tuning of power system stabilizers in a multi-machine power system using C-Catfish PSO. World Acad. Sci. Eng. Technol., 6: 770-777.

Passino, K.M., 2002. Biomimicry of bacterial foraging for distributed optimization and control. IEEE Control Syst., 22: 52-67.

Rafiee, Z. and A.F. Meyabadi, 2012. Optimal design of power system stabiliser using a new cost function and PSO algorithm. Int. J. Power Energy Convers., 3: 253-264.

Seifossadat, S.G., M. Razzaz, M. Moghaddasian and M. Monadi, 2007. Harmonic estimation in power systems using adaptive perceptrons based on a genetic algorithm. WSEAS Trans. Power Syst., 2: 239-244.

Shayeghi, H., A. Ghasemi and H. Shayanfar, 2011. PID type stabilizer design for multi machine power system using IPSO procedure. Comput. Sci. Eng., 1: 36-42.

Soliman, H.M., E.H.E. Bayoumi and M.F. Hassan, 2008. PSO-based power system stabilizer for minimal overshoot and control constraints. J. Electr. Eng., 59: 153-159.