SSRG International Journal of Electrical and Electronics Engineering
ISSN: 2348 – 8379 / https://doi.org/10.14445/23488379/IJEEE-V9I1P101

Volume 9 Issue 1, 1-9, January 2022

Original Article

Hybrid Bat Optimization Algorithm Applied to Optimal Reactive Power Dispatch Problems

S. Sakthivel Padaiyatchi[1], S. Jaya[2]

[1]*Professor, Department of Electrical and Electronics Engineering, Nehru Institute of Engineering and Technology, Coimbatore. Tamilnadu, India*
[2]*Professor, Department of Electronics and Communication Engineering Annai Veilankanni's College of Engineering, Chennai, Tamilnadu, India*

Received Date: 23 November 2021
Revised Date: 30 December 2021
Accepted Date: 01 February 2022

Abstract *- Security and economics of a power system are optimized by the control of reactive power dispatch from synchronous generators and var sources like SVCs installed in the system. Optimal reactive power dispatch (ORPD) is achieved by properly setting the value of control parameters. Generator bus voltages, transformer tap positions and SVC settings are the control parameters for reactive power optimization. Generally, artificial intelligence techniques are used for optimizing the values of control variables. In this work, a hybrid bat optimization algorithm based on particle swarm algorithm, namely HPSOBA, is proposed for reactive power optimization. This algorithm mimics the echolocation behavior of microbats. Microbats emit a kind of SONAR and wait for the echo that is bounced from the prey. The bats analyse the echo for understanding the location and size of the prey in their path. This behavior is copied in the new algorithm. The strength of this algorithm is tested by comparing its performance with that of the other bio-inspired algorithms like Biogeography Based Optimization (BBO). The test systems taken are the standard IEEE-30 bus and IEEE-57 bus systems. The results obtained are much encouraging.*

Keywords — *Optimal reactive power dispatch, Particle swarm optimization, Bat optimization algorithm, Loss minimization, VD minimization.*

I. INTRODUCTION

Reactive power or voltage control is a primary requisite for ensuring the security of power systems [1]-[2]. Reactive power control is possible by the installation of new var sources or by optimizing the reactive power output from synchronous generators and already installed var sources in the system. Non-optimized reactive power flow is indicated by increased real power loss in a power system. Minimization of real power loss is, therefore, necessary for optimal reactive power dispatch [3]. Another less important quantity that is adjusted to achieve this task is voltage deviation at load buses. The ORPD is a nonlinear, multiobjective and multi constrained optimization problem [4]-[5]. Finding the global best solution for this problem is not so easy.

The decision variables in this optimization problem are generator bus voltage magnitudes, transformer tap settings and var output from SVCs located in the system [6]-[7]. These control variables are non-continuous, and the problem has multiple minima and maxima. An efficient optimization algorithm is needed for attacking these kinds of problems.

Reactive power optimization is long being attempted by conventional optimization techniques such as Linear Programming (LP) [8], Nonlinear Programming (NLP) [9], Mixed-integer Programming (MIP) [10], Decomposition Technique (DT) [11], Dynamic Programming (DP) [12] has been studied. Gradient-based optimization algorithms have also been used to solve the ORPD problem [13]-[15]. These methods are incapable of handling nonlinear, discontinuous functions and constraints and problems having multiple local minimum points. Newton method has been successfully used in [16]–[18]. In all these techniques, simplifications have been done to overcome their limitations.

Recently, intelligence-based optimization methods have been proposed for engineering optimization problems. Wu, in [19], used Evolutionary Programming (EP) in a power system to accomplish optimal reactive power dispatch/voltage control. Lai in [20] showed EP is more capable of handling non-continuous and non-smooth functions comparing nonlinear programming. In [21], Lee has combined the Simple Genetic Algorithm (SGA) with successive linear programming for solving reactive power control problems. Particle Swarm Optimization (PSO) was applied in [22] for reactive power and voltage control considering voltage security assessment. In [23] Differential Evolutionary (DE) algorithm is implemented to the optimal reactive power dispatch problem. Mahadevan in [24] solved the ORPD problem by a Comprehensive Learning Particle Swarm Optimization Algorithm (CLPSO) approach. Other approaches for solving this problem, such as SARCGA and SOA, are introduced in [25]-[26]. For multiobjective reactive power optimization, some heuristic algorithms are used. Strength Pareto Evolutionary Algorithm (SPEA) [27]-[28] have been applied to multiobjective ORPD problems, and multiobjective differential evolution (MODE) [29] has been applied to multiobjective optimal power flow problems.

Most recently, optimization algorithms have been developed based on the food searching behavior of animals. Some animals are performing well with good intelligence in some actions. This intelligent behavior motivated researchers across the world to develop what are called bio-inspired algorithms. These bios inspired algorithms are widely exploited for power system optimization. Some of the bioinspired optimization techniques for power system optimization are Ant Colony Optimization (ACO) [30], Bacterial Foraging Algorithm (BFA) [31], FireFly Algorithm (FFA) [32], Artificial Bee Colony (ABC) Algorithm [33] and Biogeography Based Optimization (BBO) [34] algorithm. These algorithms produce encouraging results in power system related optimization.

After the successful implementation of many bio-inspired optimization algorithms, increased attention is being given to developing new bio-inspired algorithms. In this paper, the newly introduced BA algorithm is suggested for the ORPD problem. The algorithm copies the echolocation characteristics of natural bats. Bats are found to be intelligent in searching their food by analyzing the echo of the waves emitted by them.

This paper is organized as follows: the problems of reactive power and voltage control are formulated in Section 2. Section 3 explains the HPSOBA algorithm, which can be used effectively in power engineering problems. Section 4 presents numerical results and discussions. Conclusions are drawn in section 5.

II. PROBLEM FORMULATION

The objective of this work is to optimize the reactive power flow in a power system by minimizing the real power loss and the Sum of load bus voltage deviation. Therefore, an augmented objective function is formed with the two objective components along with suitable weights.

A. Objective function

The objective function of this work is the weighted sum of real power loss and voltage deviation. The design parameter values corresponding to the minimum value of the objective function are identified. Hence, the objective function can be expressed as:

$$f = \min\left[wP_L + (1-w)VD \right] \tag{1}$$

Where w is the weighing factor for real power loss and voltage deviation and is set to 0.7.

a) Real power loss minimization (PL)

The total real power of the system can be calculated as follows.

$$P_{loss} = \sum_{k=1}^{NL} G_k \left(V_i^2 + V_j^2 - 2V_iV_j \cos\left(\delta_i - \delta_j\right)\right) \tag{2}$$

Where NL is the total number of lines in the system; G_k is the conductance of line k, V_i and V_j are the magnitudes of the sending end and receiving end voltages of the line; δ_i and δ_j are angles of the end voltages.

b) Load bus voltage deviation minimization (VD)

Bus voltage magnitude should be maintained within the permissible range to ensure a quality supply of electrical power. The voltage profile is improved by minimizing the deviation of the load bus voltage from the reference value (it is taken as 1.0 p.u. in this work).

$$VD = \sum_{k=1}^{N_{PQ}} \left| \left(V_i - V_{ref} \right) \right| \tag{3}$$

B. Constraints

The minimization problem is subject to the following equality and inequality constraints

a) Equality constraints

1) Load Flow Constraints

The equality constraints represent the load flow equations, which are given below for i_{th} bus:

$$P_{Gi} - P_{Di} = \sum_{j=1}^{NB} \left(V_iV_jY_{ij}G_k \cos\left(\delta_{ij} + \gamma_j - \gamma_j\right)\right) \tag{4}$$

$$Q_{Gi} - Q_{Di} = \sum_{j=1}^{NB} \left(V_iV_jY_{ij}G_k \sin\left(\delta_{ij} + \gamma_j - \gamma_j\right)\right) \tag{5}$$

Where P_{Gi}, Q_{Gi} are the active and reactive power of i_{th} generator, P_{Di},Q_{Di} is the active and reactive power of i_{th} load bus.

b) Inequality constraints

2) Generator constraints

Generator voltage and reactive power of i_{th} bus lie between their upper and lower limits as given below:

$$V_{Gi}^{\min} \le V_{Gi} \le V_{Gi}^{\max} \qquad i = 1, 2, \ldots \ \ N_G \tag{6}$$

$$Q_{Gi}^{\min} \le Q_{Gi} \le Q_{Gi}^{\max} \qquad i = 1, 2, \ldots \ \ N_G \tag{7}$$

Where V_{Gi}^{min} and V_{Gi}^{max} are the minimum and maximum voltage of i_{th} generating unit and Q_{Gi}^{min} and Q_{Gi}^{max} are the minimum and maximum reactive power of i_{th} generating unit.

3) Load bus constraints

$$V_{PQi}^{\min} \le V_{PQi} \le V_{PQi}^{\max} \quad i = 1, 2, ... \quad N_{PQ} \tag{8}$$

Where, are the minimum and maximum value voltage of load bus *i*.

4) Transmission line constraints

$$S_{Li} \le S_{Li}^{\max} \tag{9}$$

Where S_{Li} is the apparent power flow of i_{th} branch, and S_{Li} ^{max} is the maximum apparent power flow limit of i_{th} branch.

Transformer tap settings are bounded between upper and lower limit as given below:

$$T_i^{\min} \le T_i \le T_i^{\max} \quad i = 1, 2, ... \quad N_T \tag{10}$$

Where T_i^{min} and T_i^{max} are the minimum and the minimum and maximum tap setting limits of i_{th} transformer.

5) Shunt compensator constraints

Shunt compensation is restricted by their limits as follows:

$$Q_{Ci}^{\min} \le Q_{Ci} \le Q_{Ci}^{\max} \quad i = 1, 2, ... \quad N_C \tag{11}$$

Where Q_{Gi}^{min} and Q_{Gi}^{max} are the minimum and maximum VAR injection limits of i_{th} shunt capacitor.

III. PROPOSED ALGORITHM

The basic and hybrid versions of the algorithms are discussed here. The particle best and global best solutions of particle swarm optimization algorithm are incorporated in the bat algorithm for updating the position of each bat in the hybrid version o the bat algorithm.

A. Particle Swarm Optimization (PSO)

PSO is a stochastic algorithm motivated by the social approach of animals that prefer to be in herds of flocks. PSO is extensively deployed for the achievement of the optimal solution of many engineering problems due to its flexibility and has emerged as the most effective algorithm to compute for optimization problems. PSO initializes with fixed population size (particles), and each particle is a possible potential solution in a search space. Each of these generated particles in the swarm moves to the optimal location by attaining the velocity with its position. Despite the versatility and flexibility of PSO, it gets stuck in the local minima during the solution search. Researchers have endeavored to develop the enactment of PSO by presenting new variables of the formula to regulate and control the optimal search process. Some scholars modified it by filtering the initialization of the flock, while others presented new factors such as constriction coefficient, inertia weight, and mutation operation to enhance exploitation and exploration characteristics. The two main mechanisms followed by the PSO are cognitive and social [35].

Mathematically, PSO can be represented by velocity and position formulas which are given in (12) and (13), respectively,

$$v_{id}^{t+1} = \omega v_{id}^{t} + c_1 r_1 \left(\text{pbest}_{id} - x_{id}^{t} \right) + c_2 r_2 \left(\text{gbest}_{gd} - x_{id}^{t} \right) \tag{12}$$

$$x_{id}^{t} = x_{id}^{t} + v_{id}^{t+1} \quad i = 1, 2, \ldots, n; \quad d = 1, 2, \ldots, m \tag{13}$$

Where *i*, *d*, and *t* denote the index of particles, dimension, and discrete-time index being considered, respectively. n and m represent the population of particles in a group and sizes of a particle, respectively. ω, r_1, r_2 and C_1, C_2 are inertia weight factor, randomization parameters, and social and cognitive components, respectively.

B. Bat Algorithm (BA)

BA is a progressive metaheuristic optimization technique and works on the hunting approach adopted by the micro-bats. The fundamentals of BA are derived from the echolocation-based conduct of the bats that happens according to the changing loudness and pulse rates of emission. In contrast to the other metaheuristic algorithms, BA is not controlled through mutation and crossover and provides a decent balance in exploration and exploitation mechanisms to search for a globally optimum solution.

Every bat in BA owns a location x_i^t and v_i^t velocity for iteration *t* to accomplish a solution in a *d* dimensional search space. The simulated micro-bats have a changing loudness and frequency. Each bat alters its emission rate and loudness throughout searching its prey. Prey pursuing increases through a local random walk. The selection for the optimum lasts until a stopping criterion is met. The approach follows a frequency-tuning exercise to regulate the vibrant performance of a flock of bats, and the equilibrium among exploitation and exploration can be organized through the regulation technique that depends on the factors of BA [36]. The mathematical equations of the position, frequency, and velocity are given in (14)-16),

$$f_i = f_{\min} + \left(f_{\max} - f_{\min} \right) \beta \tag{14}$$

$$v_i^{t+1} = v_i^t + \left(x_i^t - G_{\text{best}} \right) f_i \tag{15}$$

$$x_i^{t+1} = x_i^t + v_i^{t+1} \tag{16}$$

Where G_{best} is the best-approached solution and β in [0,1] is a random vector drawn from a uniform distribution.

C. Hybrid PSO and BA (HPSOBA)

PSO, in its standard form, has an issue of getting stuck in local minima that results in slower convergence and hinders the achievement of the most optimal solution. On the other hand, BA in its standard form offers better exploitation but poor exploration. Poor exploration is due to the lack of memory of the best solution found thus far during the progression of the optimization process, sometimes causing the bats to divert from promising solution search space. This requires the introduction of mechanisms that avoid such issues, and the presented algorithms resolve the above-mentioned issues.

The HPSOBA was a multipurpose and distinctive technique that combined the significant topographies of the standard PSO and BA. The designed technique offered the optimal solution of EDP for thermal, hybrid, and all RES-based plants as cited in [37]. The mathematical representation of the HPSOBA is given in (17) and (18),

$$v_{id}^{t+1} = \alpha \times \begin{bmatrix} \omega v_{id}^{t} + c_1 r_1 \left(\text{pbest}_{id} - x_{id}^{t} \right) \\ + c_2 r_2 \left(\text{gbest}_{gd} - x_{id}^{t} \right) \end{bmatrix} \tag{17}$$

$$x_i^{t+1} = (1-r) x_i^t + r\text{pbest}_i + v_i^{t+1} \tag{18}$$

The algorithm was developed using two major parameters: a new and unique parameter α and the inertial weight that were computed using (19) and (20).

$$\alpha = \left(\frac{c}{r} \right) f \tag{19}$$

$$\omega = \omega_{\min} + \left[\omega_{\max} - \left(\frac{\omega_{\min} - \omega_{\max}}{iter_{\max}} \right) iter \right] r \tag{20}$$

The designed algorithm introduced a new factor α that was computed using the random pdf r, cognitive, social component c of PSO, and frequency component of BA for the ranges used in the standard form. Generally, the researchers have considered c1 and c2. That's why these parameters have been equated to c in (29). The value of the random number r was the same for both α and ω parameters.

D. Implementation of HPSOBA for ORPD

The step by step procedure for the HPSOBA algorithm for optimal reactive power flow is explained below.

Step 1: Initialize the algorithm parameters of population size *NP;* frequency range*;* f_{max}, f_{min}, velocity bounds*;* v_{max},v_{min}, pulse rate*; r* and loudness *A*.

Step 2: Each virtual bat is represented as a vector of control variables. *i.e.* $X_i=[V_{G1},V_{G2},\ldots V_{G\ NG},T_{P1},T_{P2},\ldots T_{P\ NT}, Qc_1,Qc_2 \ldots Qc_{NC}]$. *NP* Number of virtual bats is generated randomly, respecting their limits.

Step 3: NR load flow is run, and the objective function value is calculated.

Step 4: The best objective function value is identified.

Step 5: Start the generation by creating a new virtual bat by using equations (14), (15) and (16).

Step 6: The pulse rate of the bat is compared against a randomly generated number. Once a bat approaches its prey, it reduces the loudness and increases its pulse emission rate. Thus, a bat with a low pulse rate is far away from its prey and needs to be improved (better solutions are to be identified using local search around the current best solution). Only the bat with low pulse rates are modified, and the others are retained.

Step 7: Evaluate the new solution. If the new solution is better than the current best solution, then the new solution is the current best solution. Otherwise, the old best solution is the best solution for the current iteration also.

Step 8: Repeat steps 5-7 until the convergence criterion is not met.

IV. RESULTS AND DISCUSSIONS

The effectiveness of the proposed HPSOBA based approach is tested in IEEE-30 and IEEE 57 bus systems. The algorithm parameters are tuned well to suit the proposed work. The optimal parameters of the HPSOBA algorithm are; maximum number of generations; 200, velocity limits V; [0.005, -0.005], frequency *f*; [-0.09, 0.09] and loudness limits A; [-65, 65]. Reactive power is optimized by optimally setting the values of the design variables. Generator bus voltages, transformer tap positions and settings of SVCs are the control variables or design variables. The population size is taken as 30, and the algorithm is run 20 times for obtaining the best results. The upper and lower limits of the control variables are given in table 1.

Table 1. Control variables and their limits

Control Variable	Limit
Generator voltage (V_G)	(0.9-1.1) p.u.
Tap setting (T_P)	(0.9 -1.1) p.u.
MVAR by static compensators (Q_C)	(0-30) MVAR

Three different objective functions are considered to optimize the reactive power in the system. In case '1', only real power loss is minimized, case '2' considers the optimization of voltage profile at the load buses and both real power loss and the Sum of voltage deviation are taken for reactive power optimization in case '3'.

A. IEEE-30 Bus system

IEEE-30 bus system is a medium size test system and is widely used for many powers system-related research works. The system line data and bus data are taken from [38]. The test system taken has six generating units connected to buses 1, 2, 5, 8, 11 and 13. There are 4 regulating transformers connected between bus numbers 6-9, 6-10, 4-12 and 27-28. Two shunt compensators are connected in bus numbers 10 and 24. The system is interconnected by 41 transmission lines. The dimension of this optimization problem is 12. The system is considered under baseload conditions.

a) Case 1: Minimization of Real Power Loss

Real power transmission loss minimization is the major component of reactive power optimization objectives, and it needs more attention. This case takes only the real power loss minimization as the objective function. The proposed algorithm is run, and the optimal value of total line loss is obtained. Tuned values of control variables corresponding to different objectives are given in table 2.

Table 2. Optimal control variables for IEEE-30 bus system

Parameter	Case 1	Case 2	Case 3
V_1	1.1000	0.9954	1.0589
V_2	1.0957	0.9644	1.0490
V_5	1.0771	1.0199	1.0281
V_8	1.0791	1.0177	1.0260
V_{11}	1.1000	0.9776	1.0380
V_{13}	1.1000	1.0940	1.0418
TP_{6-9}	1.0027	0.9861	0.9880
TP_{6-10}	0.9467	0.9025	1.0342
TP_{4-12}	0.9905	1.1000	1.0294
TP_{27-28}	0.9696	0.9519	0.9777
Q_{c10}	10.0000	9.0530	10.0000
Q_{c24}	10.0000	10.000	10.0000
P_L	4.6205	8.3168	5.1010
VD	1.7654	0.1346	0.3025

Real power optimization results by different algorithms are compared in table 3. It is clear that HPSOBA is performing better than the BBO and PSO algorithms. The reduction in reactive power by HPSOBA is higher by 0.3445 than by BBO. The loss minimization obtained by PSO is 5.09219 MW. HPSOBA obtains 4.6205 MW. From table 3, it is clear that HPSOBA outperforms other algorithms in the loss minimization task. The Sum of load bus voltage deviation in HPSOBA is 1.7654 MW, while BBO obtains a higher value of 2.1410.

Table 3. Minimization of objective terms (Case 1)

Parameter	Real Power loss Minimization		
	HSPOBA	BBO [34]	PSO [39]
P_{loss} (MW)	4.6205	4.9650	5.09219
VD (p.u.)	1.7654	2.1410	---

Var output from SVCs is adjusted for real power optimization. It can be seen from Table 4 that the var output required by HPSOBA is small. By way of minimizing var generation, the reactive power reserve is maximized. It results in an improved voltage stability margin. This is an additional benefit offered by HPSOBA than other algorithms compared here.

Table 4. Reactive power requirement suggested (Case 1)

Bus Number	Q requirement (MVAR)		
	HPSOBA	BBO [34]	PSO [39]
10	10.0000	28.910	15.3650
24	10.0000	10.070	6.22000

The strength of an optimization technique is usually tested by its convergence reliability and speed. The excellent convergence quality of HPSOBA is depicted in figure 1. It encourages the use of this algorithm for further research.

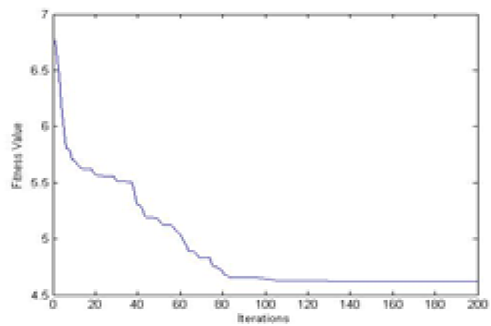

Fig 1. Convergence of HPSOBA in loss minimization in IEEE-30 system

b) Case 2: Minimization of Sum of Voltage Deviation

The objective of minimization of voltage deviation is considered in this case. The optimal settings of control variables that minimize the Sum of voltage deviation are minimized by HPSOBA and BBO algorithms. It is seen that the Sum of voltage deviation by BBO is 0.1194 p.u. This is slightly less than the voltage deviation of 0.1346 p.u. Obtained by HPSOBA. In this case, BBO performs in a better way than HPSOBA. But this is objective is not much important as loss minimization. This is for maintaining the load bus voltage at about 1.0 p.u. the voltage need not exactly be at 1.0 p.u.

Table 5. Minimization of objective terms (Case 2)

Parameter	Voltage deviation Minimization		
	HPSOBA	BBO [34]	PSO [37]
VD (p.u.)	0.1346	0.1194	0.13029
P_{loss} (MW)	8.3168	6.3766	NA

HPSOBA algorithm effectively optimizes the reactive power generation from SVCs. The total var required is 19.053 as against 21.68 suggested by BBO.

Table 6. Reactive power requirement suggested (Case 2)

Bus Number	Q requirement (MAVR)		
	HPSOBA	**BBO [34]**	**PSO [97]**
10	9.0530	9.2400	6.75000
24	10.000	12.440	4.72900

For voltage minimization, the HPSOBA algorithm takes a greater number of iterations than what was required in loss minimization. However, the algorithm converges to the optimal results. The reliability of the algorithm is proved.

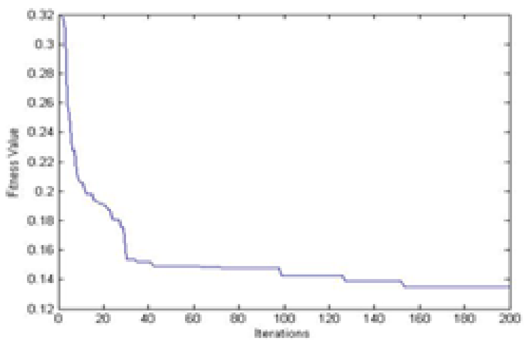

Fig. 2 Convergence of HPSOBA in VD minimization in IEEE-30 bus system

c) Case 3: Minimization of Both Real Power Loss and Voltage Deviation

Unlike the two previous cases, this case considers both real power loss and voltage deviation optimization simultaneously. This approach is most suitable for reactive power optimization as all the parameters of reactive power is included. The two objectives are augmented with proper weights. BA performs in an excellent manner in optimizing both real power loss and voltage deviation. The loss level by the BBO algorithm is only 5.6320 MW, but HPSOBA achieves 5.1010 MW. The additional saving is 0.531MW.

Table 7. Minimization of objective terms (Case 3)

Parameter	Both Real Power Loss & Voltage Deviation Minimization	
	HPSOBA	**BBO [34]**
P_{loss} (MW)	5.1010	5.6320
VD (p.u.)	0.3025	0.1549

The reduced amount of reactive power by HPSOBA, in this case, is tabulated in table 8. The convergence behavior is shown in figure 3.

Table 8. Reactive power requirement suggested (Case 3)

Bus Number	Q requirement (MVAR)	
	HPSOBA	**BBO [34]**
10	10.000	20.67
24	10.000	12.10

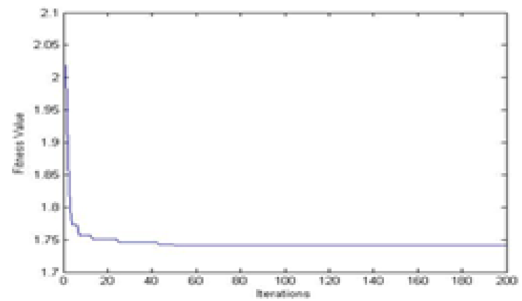

Fig. 3 Convergence of HPSOBA in loss and VD minimization in IEEE-30 bus system

B. IEEE-57 Bus system

IEEE 57-bus system has 80 branches, 7 generator buses and 15 tap setting transformers. The possible reactive power compensation buses are 18, 25 and 53. Hence there are a total of 25 control variables. The system data, variable limits and the initial values of control variables are given in [40].

a) Case 1: Minimization of Real Power Loss

The algorithm is run for minimizing the three different objectives, and the optimal parameters corresponding to the best objective function is given in table 9. The performance of the HPSOBA algorithm is compared with the seeker optimization algorithm (SOA) [41] in loss minimization.

Table 9. Optimal control parameters for IEEE-57 bus system

Parameter	Case 1	Case 2	Case 3
V_1	1.1000	1.0254	1.1000
V_2	1.1000	1.0447	1.1000
V_3	1.0398	0.9559	1.0367
V_6	1.0897	1.0124	1.0804
V_8	1.1000	1.0787	1.0896
V_9	1.0947	1.0989	1.0742
V_{12}	1.0891	0.9882	1.0720
TP_{4-18}	0.9628	1.0681	1.0577
TP_{4-18}	0.9936	0.9589	1.0469
TP_{21-20}	0.9862	0.9255	0.9819
TP_{24-26}	1.0273	0.9876	1.0108

TP_{7-29}	1.0536	1.0121	1.0248
TP_{34-32}	0.9595	0.9268	0.9505
TP_{11-41}	1.0775	0.9331	1.0205
TP_{15-45}	1.0180	0.9957	1.0102
TP_{14-46}	0.9984	0.9361	1.0227
TP_{10-51}	1.0004	1.0407	1.0187
TP_{13-49}	0.9714	0.9000	0.9808
TP_{11-43}	0.9972	0.9694	0.9771
TP_{40-56}	1.0794	1.1000	1.0321
TP_{39-57}	1.0309	1.0308	1.0278
TP_{9-55}	1.0687	1.0729	1.0515
Q_{c18}	6.0149	10.0000	5.0158
Q_{c25}	8.8052	9.9712	8.4962
Q_{c53}	6.7507	9.8828	9.9790
P_L	21.9600	32.5553	21.8904
VD	1.8666	0.7204	1.3905

SOA reports a loss of 24.26548 MW and HPSOBA 21.9600 MW. The difference in loss obtained by the algorithms is 2.30548 MW. HPSOBA shows better performance than SOA in this case. The voltage profile improvement by minimization of VD is also really good.

Table 10. Minimization of objective terms (Case 1)

Parameter	Real Power Loss Minimization	
	HPSOBA	**SOA [41]**
P_{loss} (MW)	21.9600	24.26548
VD (p.u)	1.8666	NA

As compared in the IEEE 30 bus case, the total var requirement can be considered for understanding the optimization of var level. Table 11 shows that the total var requirement by HPSOBA is less than that indicated by SOA. The advantage is that it optimizes the var reserves.

Table 11. Reactive power requirement suggested (Case 1)

Bus Number	Q requirement (MVAR)	
	HPSOBA	**SOA [41]**
18	6.0149	9.9984
25	8.8052	5.9040
53	6.7507	6.2880

Figure 4 proves the excellent convergence behavior of HPSOBA in a large power system. This is an indication that the proposed HPSOBA is suitable for all sizes of power systems and will exhibit good convergence to the best results.

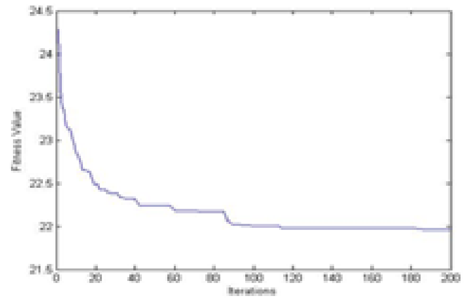

Fig. 4 Convergence of HPSOBA in loss minimization in IEEE-57 system

b) Case 2: Minimization of Sum of Voltage Deviation

Most of the previous works on ORPD with the IEEE-57 bus system considers only loss optimization. In this work, VD minimization is also considered, and the Sum of voltage deviation is given in table 12.

Table 12. Minimization of objective terms (Case 2)

Parameter	Voltage Deviation Minimization
	HPSOBA
VD (p.u)	0.7686
P_{loss} (MW)	23.4650

In this case, the algorithm suggests a var requirement which is less than 10 MVAR, as shown in table 13. Less var requirement indirectly keeps the cost of SVC minimum.

Table 13. Reactive power requirement suggested(Case 2)

Bus Number	Q requirement (MVAR)
	HPSOBA
18	7.3459
25	9.6752
53	8.5907

The algorithm takes more number iterations in VD minimization than in the other two cases. The convergence curve is shown in figure 5.

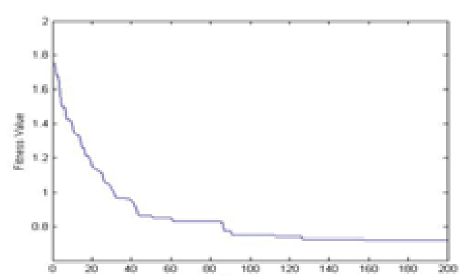

Fig. 5 Convergence of HPSOBA in VD minimization in the IEEE-57 bus system

c) Case 3: Minimization of Both Real Power Loss and Voltage Deviation

Simultaneous optimization of both VD and loss in the IEEE-57 bus system is taken for testing the performance of HPSOBA in this case. The loss minimization is 21.8904 MW, and this considerably smaller than the loss optimized by SOA in loss minimization in this system. The voltage deviation is with a very small value of 1.3905 MW. The algorithm takes about 90 iterations, and this is quite less number for a large power system.

Table 14. Minimization of objective terms (Case 3)

Parameter	**Both Real Power Loss & Voltage Deviation Minimization**
	HPSOBA
P_{loss} (MW)	22.5430
VD (p.u)	2.2746

From table 15, it is obvious that the total var needed is much lower. Var requirement, in this case, is slighter higher than the other cases.

Table 15. Reactive power requirement suggested (Case 3)

Bus Number	**Q requirement (MVAR)**
	HPSOBA
18	10.5459
25	7.8426
53	9.7807

Fig. 6 is the convergence curve of the algorithm in both loss and VD minimization. The algorithm takes about 100 iterations for achieving the best results.

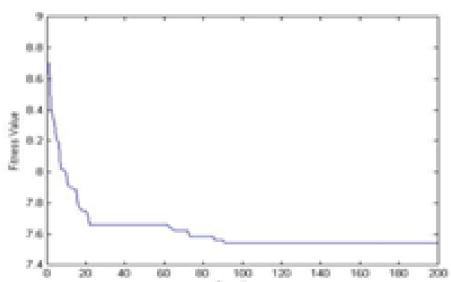

Fig. 6 Convergence of HPSOBA in loss and VD minimization in the IEEE-57 bus system

V. CONCLUSION

BA is a newly introduced bio-inspired optimization algorithm that mimics the food searching behavior of microbats. The algorithm involves no large number of operators and parameters. Tuning of the parameters for better results was found to be very simple, and this algorithm is also easy to be implemented. It is clear from the numerical results of the problem that BA outperforms the other bio-inspired algorithms like BBO in reactive power optimization. In addition to reactive power optimization, the proposed algorithm suggests only less amount of reactive power generation from SVCs installed. This maximizes the reactive power reserve and thereby improves the voltage stability limit. The convergence speed of the algorithm is also studied to understand the effectiveness of the algorithm in its task. Therefore, it is believed that this algorithm may be exploited for other power system operations like economic load dispatch, optimal power flow, voltage stability improvement etc.

REFERENCES

[1] S. Ramesh, S. Kannan, S. Baskar, Application of Modified Nsga-Ii Algorithm to Multiobjective Reactive Power Planning. Applied Soft Computing, 12 (2012) 741–753

[2] A.H. Khazali, M. Kalantar Optimal Reactive Power Dispatch Based on Harmony Search Algorithm Electrical Power and Energy Systems 33 (2011) 684–692

[3] Altaf Q.H. Badar, B.S. Umre, A.S. Junghare Reactive Power Control Using Dynamic Particle Swarm Optimization for Real Power Loss Minimization Electrical Power and Energy Systems 41 (2012) 133–136

[4] K. Mahadevan, P.S. Kannan Comprehensive Learning Particle Swarm Optimization for Reactive Power Dispatch Applied Soft Computing 10 (2010) 641–652

[5] Amit Saraswat, Ashish Saini Multiobjective Optimal Reactive Power Dispatch Considering Voltage Stability in Power Systems Using Hfmoea

[6] Serhat Duman, Ugur Guvenc, Yusuf Sönmez, Nuran Yorukeren Optimal Power Flow Using Gravitational Search Algorithm Energy Conversion And Management 59 (2012) 86–95.

[7] Bhattacharya A, Chattopadhyay Pk. Application of Biogeography-Based Optimisation to Solve Different Optimal Power Flow Problems. Iet Gener Transm Distrib 5(1) (2011) 70–80.

[8] B. Scott, J.L. Marinho, Linear Programming for Power System Network Security Applications, Ieee Transactions on Power Apparatus And Systems 98 (3) (1979) 837–845.

[9] Habiabollahzadeh H, Luo Gx, Semlyen A. Hydrothermal Optimal Power Flow Based on Combined Linear and Nonlinear Programming Methodology. Ieee Trans Power Appar Syst Pwrs 4(2) (1989) 530–7.

[10] K. Aoki, M. Fan, A. Nishikori, Optimal Var Planning by Approximation Method for Recursive Mixed-Integer Linear Programming, Ieee Transactions on Power Systems 3 (4) (1988) 1741–1747.

[11] N. Deeb, S.M. Shahidehpour, Linear Reactive Power Optimization in A Large Power Network Using the Decomposition Approach, Ieee Transactions on Power Systems 5 (2) (1990) 428–438.

[12] F.C. Lu, Y.Y. Hsu, Reactive Power/Voltage Control in A Distribution Substation using Dynamic Programming, Iee Proc. Gener., Transm. and Distrib., 142(6) (1995) 639-645.

[13] Manlovani Jrs, Garcia Av. A Heuristic Model For Reactive Power Planning. In: Ieee Trans Power Syst, 11(1) (1995) 68–74.

[14] Deeb N, Shahedipour Sm. Linear Reactive Power Optimization In A Large Power Network Using The Decomposition Approach. In: Ieee Trans Power Syst, Vol. 5, No. 2; 1990. P. 428–35.

[15] Lee Ky, Park Ym, Ortiz Jl. A United Approach To Optimal Real And Reactive Power Dispatch. In: Ieee Trans Power Syst, Vol. 1, No. 2; 1985. P. 1147–53.

[16] N. Grudinin, Reactive Power Optimization Using Successive Quadratic Programming Method, Ieee Trans. Power Syst. 13 (4) (1998) 1219–1225.

[17] K. Aoki, M. Fan, A. Nishikori, Optimal Var Planning By Approximation Method For Recursive Mixed-Integer Linear Programming, Ieee Trans. Power Syst. 3 (4) (1988) 1741–1747.

[18] D.I. Sun, B. Ashley, B. Brewer, A. Hughes, W.F. Tinmey, Optimal Power Flow By Newton Approach, Ieee Trans. Power Syst. Pas–10 (3) (1984) 2864–2880.

[19] Wu Qh, Ma Jt. Power System Optimal Reactive Power Dispatch Using Evolutionary Programming. In: Ieee Trans Power Syst, 10(3) (1995).

[20] Lai Ll, Ma Jt. Application of Evolutionary Programming to Reactive Power Planning – Comparison With Nonlinear Programming Approach. In: Ieee Trans Power Syst, 12(1) (1997) 198–206.

[21] Lee Ky, Bai X, Park Ym. Optimization Method For Reactive Power Planning By Using A Modified Simple Genetic Algorithm. In: Ieee Trans Power Syst, 10(4) (1995) 1843–50.

[22] H. Yoshida, K. Kawata, Y. Fukuyama, S. Takayama, Y. Nakanishi, A Particle Swarm Optimization For Reactive Power And Voltage Control Considering Voltage Security Assessment, Ieee Trans. Power Syst. 15 (4) (2000) 1232–1239.

[23] Varadarajan M, Swarup Ks. Differential Evolutionary Algorithm for Optimal Reactive Power Dispatch. Electric Power Energy Syst 30 (2008) 435–41.

[24] K. Mahadevan, P. S. Kannan, Comprehensive Learning Particle Swarm Optimization for Reactive Power Dispatch, Int. J. Applied Soft Computing, 10(2) (2010) 641-652.

[25] Dai Chaohua, Chen Weirong, Zhu Yunfang, Zhang Xuexia. Seeker Optimization Algorithm for Optimal Reactive Power Dispatch. in: Ieee Trans On Power Syst, 24(3)(2009).

[26] Subbaraj P, Rajnarayanan Pn. Optimal Reactive Power Dispatch Using Self-Adaptive Real Coded Genetic Algorithm. Electr Power Syst Res 79(2009) 374–81.

[27] Sailaja Kumari M, Maheswarapu S. Enhanced Genetic Algorithm Based Computation Technique for Multiobjective Optimal Power Flow Solution. Int J Electr Power Energy Syst 32(6) (2010) 736–42.

[28] Abido Ma, Bakhashwain Jm. Optimal Var Dispatch Using A Multiobjective Evolutionary Algorithm. Int J Electr Power Energy Syst 27(1) (2005) 13–20.

[29] Varadarajan M, Swarup Ks. Solving Multi-Objective Optimal Power Flow Using Differential Evolution. Iee Proc Gener Transm Distrib 2(5) (2008) 720–30.

[30] Kursat Ayan, Ulas¸ Kılıc¸ Artificial Bee Colony Algorithm Solution For Optimal Reactive Power flow Applied Soft Computing 12 (2012) 1477–1482.

[31] Tripathy, M. Mishra, S.Bacteria Foraging-Based Solution to Optimize Both Real Power Loss and Voltage Stability Limit Power Systems, Ieee Transactions on 22(1) 240 – 248.

[32] Theofanis Apostolopoulos, Aristidis Vlachos Application Of The Firefly Algorithm For Solving The Economic Emissions Load Dispatch Problem International Journal Of Combinatorics Volume Article Id 523806, (2011) 23.

[33] S.Hemamalini and SishajP.SimonArtificial Bee Colony Algorithm for Economic Load Dispatch Problem With Non-Smooth Cost Functions 38(7) (2010) 786-803.

[34] P.K. Roy, S.P. Ghoshal, S.S. Thakur Optimal Var Control for Improvements in Voltage Profiles and for Real Power Loss Minimization using Biogeography Based Optimization Electrical Power and Energy Systems 43 (2012) 830–838.

[35] Wang, Dongshu, Dapei Tan, And Lei Liu. Particle Swarm Optimization Algorithm: An Overview. Soft Computing 22 (2) (2018) 387-408.

[36] Xin-She Yang, Amir H. Gandomi Bat Algorithm: A Novel Approach for Global Engineering Optimization Engineering Computations, V29, (5) (2012) 464-483

[37] Ellahi, Manzoor, Ghulam Abbas, Gandeva Bayu Satrya, M. Rehan Usman, and Jason Gu. A Modified Hybrid Particle Swarm Optimization with Bat Algorithm Parameter Inspired Acceleration Coefficients for Solving Eco-Friendly and Economic Dispatch Problems. Ieee Access 9 (2021): 82169-82187.

[38] Ieee 30 Bus Test System, Http://Www.Ee.Washington.Edu/Research/Pstca/Pf30/Ieee30cdf.Txt

[39] Vlachogiannis J G, Lee K Y. A Comparative Study On Particle Swarm Optimization For The Optimal Steady-State Performance Of Power Systems. Ieee Trans Power Syst 21(4) (2006) 1718–28.

[40] Ieee 57 Bus Test System, Http://Www.Ee.Washington.Edu/Research/Pstca/Pf57/Ieee57cdf.Txt

[41] Chaohua Dai, Weirong Chen, Yunfang Zhu, Xuexia Zhang, Seeker Optimization Algorithm For Optimal Reactive Power Dispatch Ieee Transactions On Power Systems, 24(3) 2009.