Minimization of real power loss by enhanced teaching learning based optimization algorithm

K. Lenin
Department of EEE Prasad V. Potluri Siddhartha Institute of Technology, India

Article Info

Article history:

Received Dec 07, 2017
Revised Oct 06, 2019
Accepted Oct 31, 2019

Keywords:

Enhanced teaching learning
Optimal reactive power
Transmission loss

ABSTRACT

This paper presents an Enhanced Teaching-Learning-Based Optimization (ETLBO) algorithm for solving reactive power flow problem. Teaching-learning process is an iterative process where in the continuous interaction takes place for the transfer of knowledge. Movements of trial solutions will investigate the internally final stages. Up gradation of the algorithm has been done through by adding weight in the learner values. Projected ETLBO algorithm has been tested in standard IEEE 57,118 bus systems and power loss has been reduced efficiently.

Corresponding Author:

K. Lenin,
Department of EEE,
Prasad V. Potluri Siddhartha Institute of Technology,
Kanuru, Vijayawada, Andhra Pradesh, India.
Email: gklenin@gmail.com

1. INTRODUCTION

Optimal reactive power dispatch problem is one of the difficult optimization problems in power systems & various mathematical techniques [1-9] have been utilized to solve the problem. Recently many types of Evolutionary algorithms [10-15] have been used to solve the reactive power problem. This paper presents an Enhanced Teaching-Learning-Based Optimization (ETLBO) algorithm for solving reactive power flow problem. Basic Teaching-Learning-Based Optimization [16] successfully solved various optimization problems. In this projected work new learner values the part of its previous value is considered and it has been decided by a weight factor "wf". During the early stages of the search Individuals are encouraged to sample diverse zones of the exploration space. Projected ETLBO algorithm has been tested in standard IEEE 57,118 bus systems and real power loss has been reduced.

2. PROBLEM FORMULATION

Reduction real power loss is the key goal of the work and the objective function has been written as follows (1):

$$F = P_L = \sum_{k \in Nbr} g_k \left(V_i^2 + V_j^2 - 2V_i V_j \cos\theta_{ij}\right) \tag{1}$$

Voltage deviation mathematically written as (2-3),

$$F = P_L + \omega_v \times \text{Voltage Deviation} \tag{2}$$

$$\textbf{Voltage Deviation} = \sum_{i=1}^{Npq} |V_i - 1| \tag{3}$$

Constraint (Equality) (4):

$$P_G = P_D + P_L \tag{4}$$

Constraints (Inequality) (5-9):

$$P_{gslack}^{min} \le P_{gslack} \le P_{gslack}^{max} \tag{5}$$

$$Q_{gi}^{min} \le Q_{gi} \le Q_{gi}^{max}, i \in N_g \tag{6}$$

$$V_i^{min} \le V_i \le V_i^{max}, i \in N \tag{7}$$

$$T_i^{min} \le T_i \le T_i^{max}, i \in N_T \tag{8}$$

$$Q_c^{min} \le Q_c \le Q_C^{max}, i \in N_C \tag{9}$$

3. ENHANCED TEACHING-LEARNING-BASED OPTIMIZATION ALGORITHM

Basic Teaching-Learning-Based Optimization Algorithm consist of first part "Teacher Phase" and the second "Learner Phase". Learning from the teacher is the "Teacher Phase" means and learning through the interaction between learners is the "Learner Phase". In search space bounded the population *Y* is arbitrarily initialized by (10-11):

$$y_{(i,j)}^0 = y_j^{min} + rand \times \left(y_j^{max} - y_j^{min}\right) \tag{10}$$

$$Y_{(i)}^g = \left[y_{(i,1)}^g, y_{(i,2)}^g, y_{(i,3)}^g, \ldots, y_{(i,j)}^g, \ldots, y_{(i,D)}^g\right] \tag{11}$$

3.1. Teacher phase

At generation *g* the mean parameter E_g of each subject learners in the class is given as (12):

$$E^g = \left[e_1^g, e_2^g, \ldots, e_j^g, \ldots, e_D^g\right] \tag{12}$$

A new-fangled set of improved learners is added to the existing population of learners (13-14).

$$Ynew_{(i)}^g = Y_{(i)}^g + rand \times \left(Y_{Teacher}^g - Te_F E^g\right) \tag{13}$$

$$Te_F = round\ [1 + rand\ (0.1)\ \{2 - 1\}] \tag{14}$$

3.2. Learner phase

Knowledge of the learner is improved by (15),

$$Y_{(i)}^g = \begin{cases} Y_{(i)}^g + rand \times \left(Y_{(i)}^g - Y_{(r)}^g\right) \\ \quad if\ f\left(Y_{(i)}^g\right) < f\left(Y_{(r)}^g\right) \\ Y_{(i)}^g + rand \times \left(Y_{(r)}^g - Y_{(i)}^g\right) otherwise \end{cases} \tag{15}$$

3.3. Algorithm termination

After *MAXIT* conditions satisfied the algorithm is terminated. Value of the weight factor reduced linearly with time from a maximum to a minimum value by (16),

$$wf = wf_{max} - \left(\frac{wf_{max} - wf_{min}}{\max iteration}\right) * i \tag{16}$$

Enhanced learners in the teacher phase can be (17),

$$Ynew_{(i)}^{g} = wf * Y_{(i)}^{g} + rand * \left(Y_{Teacher}^{g} - Te_{F}E^{g}\right) \quad (17)$$

And in learner phase a set of improved learners are (18),

$$Ynew_{(i)}^{g} = \begin{cases} wf * X_{(i)}^{g} + rand \times \left(Y_{(i)}^{g} - Y_{(r)}^{g}\right) \\ \quad if\ f\left(Y_{(i)}^{g}\right) < f\left(Y_{(r)}^{g}\right) \\ wf * Y_{(i)}^{g} + rand \times \left(Y_{(r)}^{g} - Y_{(i)}^{g}\right) otherwise \end{cases} \quad (18)$$

4. SIMULATION RESULTS

At first Enhanced Teaching-Learning-Based Optimization (ETLBO) algorithm has been tested in standard IEEE-57 bus power system. 18, 25 and 53 are the reactive power compensation buses. PV buses are 2, 3, 6, 8, 9 and 12 and bus 1 is slack-bus. In Table 1 The system variable limits are given. The preliminary conditions for the IEEE-57 bus power system are given as follows:

P_{load} =12.126 p.u. Q_{load}=3.064 p.u.

The total initial generations and power losses are obtained as follows:

$\sum P_G$ = 12.478 p.u. $\sum Q_G$=3.3165 p.u.

P_{loss} = 0.25886 p.u. Q_{loss}=-1.2081 p.u.

Table 2 shows the comparison of optimum results. Table 3 shows the various system control variables.

Table 1. Variable limits

Reactive power generation limits							
Bus no	1	2	3	6	8	9	12
Qgmin	-1.4	-.015	-.02	-0.04	-1.3	-0.03	-0.4
Qgmax	1	0.3	0.4	0.21	1	0.04	1.50
Voltage and tap setting limits							
vgmin	Vgmax	vpqmin	Vpqmax	tkmin	tkmax		
0.9	1.0	0.91	1.05	0.9	1.0		
Shunt Capacitor Limits							
Bus no	18	25	53				
Qcmin	0	0	0				
Qcmax	10	5.2	6.1				

Table 2. Comparison results

S.No.	Optimization algorithm	Finest solution	Poorest solution	Normal solution
1	NLP [17]	0.25902	0.30854	0.27858
2	CGA [17]	0.25244	0.27507	0.26293
3	AGA [17]	0.24564	0.26671	0.25127
4	PSO-w [17]	0.24270	0.26152	0.24725
5	PSO-cf [17]	0.24280	0.26032	0.24698
6	CLPSO [17]	0.24515	0.24780	0.24673
7	SPSO-07 [17]	0.24430	0.25457	0.24752
8	L-DE [17]	0.27812	0.41909	0.33177
9	L-SACP-DE [17]	0.27915	0.36978	0.31032
10	L-SaDE [17]	0.24267	0.24391	0.24311
11	SOA [17]	0.24265	0.24280	0.24270
12	LM [18]	0.2484	0.2922	0.2641
13	MBEP1 [18]	0.2474	0.2848	0.2643
14	MBEP2 [18]	0.2482	0.283	0.2592
15	BES100 [18]	0.2438	0.263	0.2541
16	BES200 [18]	0.3417	0.2486	0.2443
17	Proposed ETLBO	0.22048	0.23012	0.22282

Table 3. Control variables obtained after optimization

Control Variables	ETLBO
V1	1.1
V2	1.0350
V3	1.0340
V6	1.0280
V8	1.0200
V9	1.0090
V12	1.0160
Qc18	0.06620
Qc25	0.2000
Qc53	0.04710
T4-18	1.0090
T21-20	1.0460
T24-25	0.8640
T24-26	0.8720
T7-29	1.0500
T34-32	0.8700
T11-41	1.0120
T15-45	1.0300
T14-46	0.9100
T10-51	1.0200
T13-49	1.0600
T11-43	0.9100
T40-56	0.9000
T39-57	0.9500
T9-55	0.9500

Then Enhanced Teaching-Learning-Based Optimization (ETLBO) algorithm has been tested in standard IEEE 118-bus test system [19]. The system has 54 generator buses, 64 load buses, 186 branches and 9 of them are with the tap setting transformers. The limits of voltage on generator buses are 0.95-1.1 per-unit., and on load buses are 0.95-1.05 per-unit. The limit of transformer rate is 0.9-1.1, with the changes step of 0.025. With the change in step of 0.01the limitations of reactive power source are listed in Table 4. The statistical comparison results of 50 trial runs have been list in Table 5 and the results clearly show the better performance of proposed Enhanced Teaching-Learning-Based Optimization (ETLBO) algorithm in reducing the real power loss.

Table 4. Limitation of reactive power sources

BUS	5	34	37	44	45	46	48
QCMAX	0	14	0	10	10	10	15
QCMIN	-40	0	-25	0	0	0	0
BUS	74	79	82	83	105	107	110
QCMAX	12	20	20	10	20	6	6
QCMIN	0	0	0	0	0	0	0

Table 5. Comparison results

Active power loss (MW)	BBO [20]	ILSBBO/strategy1 [20]	ILSBBO/strategy1 [20]	Proposed ETLBO
Min	128.77	126.98	124.78	116.120
Max	132.64	137.34	132.39	120.340
Average	130.21	130.37	129.22	117.040

5. CONCLUSION

In this work Enhanced Teaching-Learning-Based Optimization (ETLBO) algorithm solved the optimal reactive power problem. A parameter called as “weight” has been included in the basic Teaching-Learning based algorithm. The performance of the proposed Enhanced Teaching-Learning-Based Optimization (ETLBO) algorithm has been has been tested in standard IEEE 57,118 bus systems and real power loss considerably reduced.

REFERENCES

[1] O. Alsac and B. Scott, "Optimal load flow with steady state security," IEEE Transaction. PAS -1973, pp. 745-751.
[2] Lee K. Y., Paru Y. M., Oritz J. L., "A united approach to optimal real and reactive power dispatch," IEEE Transactions on power Apparatus and systems 1985: PAS-104 : 1147-1153.
[3] A. Monticelli, M. V. F. Pereira, and S. Granville, "Security constrained optimal power flow with post contingency corrective rescheduling," IEEE Transactions on Power Systems: PWRS-2, No. 1, pp.175-182., 1987.
[4] Deeb N., Shahidehpur S. M ,Linear reactive power optimization in a large power network using the decomposition approach. IEEE Transactions on power system 1990: 5(2): 428-435.
[5] E. Hobson ,'Network consrained reactive power control using linear programming, ' IEEE Transactions on power systems PAS -99 (4) ,pp 868=877, 1980.
[6] K. Y Lee ,Y. M Park , and J. L. Oritz, "Fuel –cost optimization for both real and reactive power dispatches" , IEE Proc; 131C,(3), pp.85-93.
[7] M. K. Mangoli, and K. Y. Lee, "Optimal real and reactive power control using linear programming," Electr.Power Syst.Res, Vol.26, pp.1-10, 1993.
[8] S. Granville. "Optimal reactive dispatch through interior point methods," IEEE Transactions on Power System, vol/issue: 9(1), pp. 136–146, http://dx.doi.org/10.1109/59.317548, 1994.
[9] Aparajita Mukherjee, Vivekananda Mukherjee, "Solution of optimal reactive power dispatch by chaotic krill herd algorithm," IET Gener. Transm. Distrib, Vol. 9, Issue. 15, pp. 2351–2362, 2015.
[10] Hu, Z., Wang, X. & Taylor, G. Stochastic optimal reactive power dispatch: Formulation and solution method. Electr. Power Energy Syst., vol. 32, pp. 615-621. 2010.
[11] Mahaletchumi A/P Morgan , Nor Rul Hasma Abdullah, Mohd Herwan Sulaiman, Mahfuzah Mustafa and Rosdiyana Samad, "Computational intelligence technique for static VAR compensator (SVC) installation considering multi-contingencies (N-m)", ARPN Journal of Engineering and Applied Sciences VOL. 10, NO. 22, December 2015.
[12] Mohd Herwan Sulaiman, Zuriani Mustaffa, Hamdan Daniyal, Mohd Rusllim Mohamed and Omar Aliman, "Solving Optimal Reactive Power Planning Problem Utilizing Nature Inspired Computing Techniques", ARPN Journal of Engineering and Applied Sciences VOL. 10, NO. 21, pp.9779-9785. November 2015.
[13] Mohd Herwan Sulaiman, Wong Lo Ing, Zuriani Mustaffa and Mohd Rusllim Mohamed, "Grey Wolf Optimizer for Solving Economic Dispatch Problem with Valve-Loading Effects", ARPN Journal of Engineering and Applied Sciences VOL. 10, NO. 21, , pp. 9796-9801, NOVEMBER 2015.
[14] Pandiarajan, K. & Babulal, C. K., "Fuzzy harmony search algorithm based optimal power flow for power system security enhancement". International Journal Electric Power Energy Syst., vol. 78, pp. 72-79. 2016.
[15] Mustaffa, Z., Sulaiman, M.H., Yusof, Y., Kamarulzaman, S.F., "A novel hybrid metaheuristic algorithm for short term load forecasting", International Journal of Simulation: Systems, Science and Technology, Volume 17, Issue 41, Pages 6.1-6.6. 2017.
[16] R. V. Rao, V. J. Savsani and D. P. Vakharia, "Teaching- Learning-Based Optimization: A Novel Method for Con- strained Mechanical Design Optimization Problems," Computer-Aided Design, Vol. 43, No. 1, 2011, pp. 303- 315. doi:10.1016/j.cad.2010.12.015.
[17] Chaohua Dai, Weirong Chen, Yunfang Zhu, and Xuexia Zhang, "Seeker optimization algorithm for optimal reactive power dispatch," IEEE Trans. Power Systems, Vol. 24, No. 3, August 2009, pp. 1218-1231.
[18] J. R. Gomes and 0. R. Saavedra, "Optimal reactive power dispatch using evolutionary computation: Extended algorithms," IEE Proc.-Gener. Transm. Distrib.. Vol. 146, No. 6. Nov. 1999.
[19] IEEE, "The IEEE 30-bus test system and the IEEE 118-test system", (1993), http://www.ee.washington.edu/trsearch/pstca/.
[20] Jiangtao Cao, Fuli Wang and Ping Li, "An Improved Biogeography-based Optimization Algorithm for Optimal Reactive Power Flow" International Journal of Control and Automation Vol.7, No.3 (2014), pp.161-176.