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LESSENING OF ACTUAL POWER LOSS BY MODIFIED ALGORITHM

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Abstract

This paper presents a Modified Teaching-Learning-Based Optimization (MTLBO) algorithm for solving reactive power flow problem. Basic Teaching-Learning-Based Optimization (TLBO) is reliable, accurate and vigorous for solving the optimization problems. Also, it has been found that TLBO algorithm slow in convergence due to its high concentration in the accuracy. This paper presents an, Modified version of TLBO algorithm, called as Modified Teaching-Learning-Based Optimization (MTLBO). A parameter called as "weight" has been included in the fundamental TLBO equations & subsequently it increases the rate of convergence. In order to evaluate the proposed algorithm, it has been tested in practical 191 test bus system. Simulation results reveal about the better performance of the proposed algorithm in reducing the real power loss & voltage profiles are within the limits.

Keywords: Optimal Reactive Power; Transmission Loss; Modified Teaching Learning.

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1. Introduction

Optimal reactive power dispatch problem is one of the difficult optimization problems in power systems & various mathematical techniques [1-7] have been utilized to solve the problem. Recently many types of Evolutionary algorithms [8-9] have been used to solve the reactive power problem. This paper presents a Modified Teaching-Learning-Based Optimization (MTLBO) algorithm for solving reactive power flow problem. Basic Teaching-Learning-Based Optimization (TLBO) [10-16] is reliable, accurate and vigorous for solving the optimization problems. Also it has been found that TLBO algorithm slow in convergence due to its high concentration in the accuracy. This paper presents an, Modified version of TLBO algorithm, called as Modified Teaching-Learning-Based Optimization (MTLBO). A parameter called as "weight" has been included in the fundamental TLBO equations & subsequently it increases the rate of convergence. In order to evaluate the proposed algorithm, it has been tested in practical 191 test bus system. Simulation results reveal about the better performance of the proposed algorithm in reducing the real power loss & voltage profiles are within the limits.

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2. Objective Function

Active Power Loss

The objective of the reactive power dispatch is to minimize the active power loss in the transmission network, which can be described as follows:

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

Where F- objective function, P_L – power loss, g_k-conductance of branch,V_i and V_j are voltages at buses i,j,Nbr- total number of transmission lines in power systems.

Voltage Profile Improvement

For minimizing the voltage deviation in PQ buses, the objective function becomes:

$$F = PL + \omega_v \times VD \quad (2)$$

Where VD - voltage deviation,ω_v- is a weighting factor of voltage deviation.

Voltage deviation given by:

$$VD = \sum_{i=1}^{Npq} |V_i - 1| \quad (3)$$

Where Npq- number of load buses

Equality Constraint

The equality constraint of the problem is represented by the power balance equation, where the total power generation must cover the total power demand and the power losses:

$$P_G = P_D + P_L \quad (4)$$

Where P_G- total power generation,P_D - total power demand.

Inequality Constraints

The inequality constraints in the power system as well as the limits created to ensure system security. Upper and lower bounds on the active power of slack bus (Pg), and reactive power of generators (Q_g) are written in mathematically as follows:

$$P_{gslack}^{min} \le P_{gslack} \le P_{gslack}^{max} \quad (5)$$

$$Q_{gi}^{min} \le Q_{gi} \le Q_{gi}^{max}, i \in N_g \quad (6)$$

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Upper and lower bounds on the bus voltage magnitudes (V_i):

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

Upper and lower bounds on the transformers tap ratios (T_i):

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

Upper and lower bounds on the compensators reactive powers (Q_c):

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

Where N is the total number of buses, N_T is the total number of Transformers; N_c is the total number of shunt reactive compensators.

3. Basic Teaching-Learning-Based Optimization

Based on the consequence of the influence of a teacher on the output of students in a class, Teaching-Learning-Based Optimization (TLBO) optimization algorithm has been framed. It is a population-based method & there are numbers of different design variables. Different subjects offered to learners and the learners' result is analogous to the "fitness" & it act as different design variables in TLBO. The most excellent solution is analogous to Teacher in TLBO. The algorithm consists 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". The execution of TLBO as follows,

1) Initialization

Following are the notations used for describing the TLBO:
L: "class size "of the learners;
C: list of the courses offered to the learners to learn;
MAX IT; number of maximum iterations.
In search space bounded the population *Y* is arbitrarily initialized by a by matrix of *L* rows and *C* columns. In *ith* learner . the *jth* parameter is assigned values arbitrarily by equation

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

Within the range (0,1) "*rand*" represents a uniformly distributed arbitrary variable, minimum and maximum value for *jth* parameter is represented by y_j^{max} and y_j^{min}. For the generation *g* parameters of the *ith* learner are given by,

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

2) Teacher Phase

At generation g the mean parameter E_g of each subject learners in the class is given as,

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

The teacher $X_{Teacher}^g$ with the minimum objective function value of the learner is considered as for respective iteration. Shifting the mean of the learners towards its teacher is done by Teacher phase. An arbitrary weighted differential vector is formed to obtain a new-fangled set of improved learners from the current mean, desired mean parameters and is added to the existing population of learners.

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

The value of mean to be changed is decided by "Te_F" - teaching factor. Value of T_F can be either 1 or 2. With equal probability the value of Te_F is decided arbitrarily as,

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

The value of T_F value is arbitrarily decided by the algorithm using Equation (14). In generation g if $Ynew_{(i)}^g$ is superior learner than $Y_{(i)}^g$, than it swap the inferior learner $Y_{(i)}^g$ in the matrix.

3) Learner Phase

In this phase the mutual interaction tends to augment the knowledge of the learner. The arbitrary inter- action among learners improves the knowledge. For a given learner $Y_{(i)}^g$ another learner $Y_{(r)}^g$ is arbitrarily selected$(i \neq r)$. In the learner phase the *ith* parameter of the matrix Y_{new} is given as,

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

4) Algorithm Termination

After *MAXIT* conditions satisfied the algorithm is terminated.

4. Modified Teaching-Learning-Based Optimization (MTLBO) Algorithm

The principles of teaching-learning approach is imitated in Teaching-Learning-Based Optimization (TLBO) & draw analogy with the real class room. Teaching-learning process is an iterative process where in the continuous interaction takes place for the transfer of knowledge. A parameter known as "weight" is added in the Equations (13) and (15) of original TLBO algorithm. In contrast to the original TLBO, while computing the new learner values the part of its previous

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value is considered and decided by a weight factor "*wf*" in our Modified Teaching-Learning-Based Optimization (MTLBO) algorithm. During the early stages of the search Individuals are encouraged to sample diverse zones of the exploration space. It is important to adjust the movements of trial solutions finely & they can explore the interior of a relatively small space in the later stages. Value of the weight factor reduced linearly with time from a maximum to a minimum value by,

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

The maximum and minimum values of weight factor *w* are wf_{max} and wf_{min} , "*I*" - iteration is the current iteration number and max iteration is the maximum number of iterations. wf_{max} & wf_{min} are selected between 0.9 -0.1, respectively. New set of improved learners in the teacher phase can be,

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

And in learner phase a set of improved learners are,

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

5. Simulation Results

Modified Teaching-Learning-Based Optimization (**MTLBO**) algorithm has been tested in practical 191 test system and the following results have been obtained. In Practical 191 test bus system – Number of Generators = 20, Number of lines = 200, Number of buses = 191 Number of transmission lines = 55. Table 1 shows the optimal control values of practical 191 test system obtained by MTLBO method. And table 2 shows the results about the value of the real power loss by obtained by **Modified** Teaching-Learning-Based Optimization (**MTLBO**) algorithm.

Table 1: Optimal Control values of Practical 191 utility (Indian) system by MTLBO method

VG1	1.1000		VG 11	0.9000
VG 2	0.7200		VG 12	1.0000
VG 3	1.0100		VG 13	1.0000
VG 4	1.0100		VG 14	0.9000
VG 5	1.1000		VG 15	1.0000
VG 6	1.1000		VG 16	1.0000
VG 7	1.1000		VG 17	0.9000
VG 8	1.0100		VG 18	1.0000
VG 9	1.1000		VG 19	1.1000
VG 10	1.0100		VG 20	1.1000

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T1	1.0000		T21	0.9000		T41	0.9000
T2	1.0000		T22	0.9000		T42	0.9000
T3	1.0000		T23	0.9000		T43	0.9100
T4	1.1000		T24	0.9000		T44	0.9100
T5	1.0000		T25	0.9000		T45	0.9100
T6	1.0000		T26	1.0000		T46	0.9000
T7	1.0000		T27	0.9000		T47	0.9100
T8	1.0100		T28	0.9000		T48	1.0000
T9	1.0000		T29	1.0100		T49	0.9000
T10	1.0000		T30	0.9000		T50	0.9000
T11	0.9000		T31	0.9000		T51	0.9000
T12	1.0000		T32	0.9000		T52	0.9000
T13	1.0100		T33	1.0100		T53	1.0000
T14	1.0100		T34	0.9000		T54	0.9000
T15	1.0100		T35	0.9000		T55	0.9000

Table 2**:** Optimum real power loss values obtained for practical 191 utility (Indian) system by MTLBO method.

Real power Loss (MW)	**MTLBO**
Min	149.1213
Max	154.1298
Average	151.2010

6. Conclusion

In this paper a novel approach Modified Teaching-Learning-Based Optimization (MTLBO) algorithm used to solve reactive power problem, considering various generator constraints, has been successfully applied. Also it has been found that TLBO algorithm slow in convergence due to its high concentration in the accuracy. The performance of the proposed Modified Teaching-Learning-Based Optimization (MTLBO) algorithm has been has been tested in **practical 191 test bus system** and simuation results expose about the decrease of real power loss & volatge profiles are within the limits.

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] K.Anburaja, “Optimal power flow using refined genetic algorithm”, Electr.Power Compon.Syst , Vol. 30, 1055-1063,2002.
[9] D. Devaraj, and B. Yeganarayana, “Genetic algorithm based optimal power flow for security enhancement”, IEE proc-Generation.Transmission and. Distribution; 152, 6 November 2005.
[10] 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 .
[11] R. V. Rao, V. J. Savsani and D. P. Vakharia, “Teach- ing-Learning-Based Optimization: An Optimization Me- thod for Continuous Non-Linear Large Scale Problems,” INS 9211 No. of Pages 15, Model 3G 26 August 2011.
[12] R. V. Rao, V. J. Savsani and J. Balic, “Teaching Learning Based Optimization Algorithm for Constrained and Un- constrained Real Parameter Optimization Problems,” En- gineering Optimization, Vol. 44, No. 12, 2012, pp. 1447- 1462. doi:10.1080/0305215X.2011.652103.
[13] R. V. Rao and V. J. Savsani, “Mechanical Design Opti- mization Using Advanced Optimization Techniques,” Springer-Verlag, London, 2012. doi:10.1007/978-1-4471-2748-2
[14] V. Toğan, “Design of Planar Steel Frames Using Teach- ing-Learning Based Optimization,” Engineering Struc- tures, Vol. 34, 2012, pp. 225-232. doi:10.1016/j.engstruct.2011.08.035
[15] R. V. Rao and V. D. Kalyankar, “Parameter Optimization of Machining Processes Using a New Optimization Algo- rithm,” Materials and Manufacturing Processes, Vol. 27, No. 9, 2011, pp. 978-985. doi:10.1080/10426914.2011.602792.
[16] S. C. Satapathy and A. Naik, “Data Clustering Based on Teaching-Learning-Based Optimization. Swarm, Evolu- tionary, and Memetic Computing,” Lecture Notes in Com- puter Science, Vol. 7077, 2011, pp. 148-156, doi:10.1007/978-3-642-27242-4_18.

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