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Advanced teaching-learning-based optimization algorithm for actual power loss reduction

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ABSTRACT

In this work Advanced Teaching-Learning-Based Optimization algorithm (ATLBO) is proposed to solve the optimal reactive power problem. Teaching-Learning-Based Optimization (TLBO) optimization algorithm has been framed on teaching learning methodology happening in classroom. Algorithm consists of “Teacher Phase”, “Learner Phase”. In the proposed Advanced Teaching-Learning-Based Optimization algorithm non-linear inertia weighted factor is introduced into the fundamental TLBO algorithm to manage the memory rate of learners. In order to control the learner’s mutation arbitrarily during the learning procedure a non-linear mutation factor has been applied. Proposed Advanced Teaching-Learning-Based Optimization algorithm (ATLBO) has been tested in standard IEEE 14, 30 bus test systems and simulation results show the proposed algorithm reduced the real power loss effectively.

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1. INTRODUCTION

Reactive power problem plays an important role in secure and economic operations of power system. Numerous types of methods [1-6] have been utilized to solve the optimal reactive power problem. However many scientific difficulties are found while solving problem due to an assortment of constraints. Evolutionary techniques [7-16] are applied to solve the reactive power problem. This paper proposes Advanced Teaching-Learning-Based Optimization algorithm (ATLBO) to solve optimal reactive power problem. Teaching-Learning-Based Optimization (TLBO) optimization algorithm has been framed on teaching learning methodology happening in classroom. Algorithm consists of “Teacher Phase”, “Learner Phase”. In the proposed Advanced Teaching-Learning-Based Optimization algorithm (ATLBO) non-linear inertia weighted factor is introduced into the fundamental TLBO algorithm to manage the memory rate of learners. In order to control the learner’s mutation arbitrarily during the learning procedure a non-linear mutation factor has been applied. Preceding information gathering of learners is determined by the weight factor ω_c and through that new-fangled values are calculated. In a learning cycle individuals will try to explore various regions of the exploration space in initial phase. Afterwards individuals progress in a little range to regulate the trial solution to certain extent such that it can investigate reasonably little local space. Proposed Advanced Teaching-Learning-Based Optimization algorithm (ATLBO) has been tested in standard IEEE 14, 30, bus test systems and simulation results show the projected algorithm reduced the real power loss effectively.

2. PROBLEM FORMULATION

Objective of the problem is to reduce the true power loss:

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

Voltage deviation given as follows:

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

Voltage deviation given by:

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

Constraint (equality):

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

Constraints (inequality):

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

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

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

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

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

3. ADVANCED TEACHING-LEARNING-BASED OPTIMIZATION ALGORITHM

Teaching-Learning-Based Optimization (TLBO) optimization algorithm has been framed on teaching learning methodology happening in classroom. Algorithm consists of "Teacher Phase", "Learner Phase" [17].

In *ith* learner the *jth* parameter is assigned values capriciously found by

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

For the production "g" parameters of the *ith* learner are given by,

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

3.1. Teacher Phase

Creation of "g" ; mean parameter E_g of each subject learners in the class is defined by,

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

New set of better learners are found by

$$Xnew_{(i)}^g = X_{(i)}^g + random \times \left(X_{Teacher}^g - Te_F E^g\right) \tag{13}$$

Value of mean to be altered is decided by "Te_F" - teaching factor. Value of Te_F can be 1 or 2.

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

3.2. Learner Phase

For a specified learner $X_{(i)}^g$ a different learner $X_{(r)}^g$ is capriciously chosen$(i \ne r)$. In the learner stage the X_{new} is given as:

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

In the proposed Advanced Teaching-Learning-Based Optimization algorithm (ATLBO) non-linear inertia weighted factor is introduced into the fundamental TLBO algorithm to manage the memory rate of learners. In order to control the learner's mutation arbitrarily during the learning procedure a non-linear mutation factor has been applied. Preceding information gathering of learners is determined by the weight factor ω_c and through that new-fangled values are calculated. T is number of iteration in single learning cycle. Then the inertia weight factor is described by,

$$\omega_c = 1 - exp\left(\frac{-\left(mod(iter,T)\right)^2}{2\times(T/8)^2}\right) \times (1 - \omega_{c\ minimum}), T \leq maximum\ iteration \tag{16}$$

In a learning cycle individuals will try to explore various regions of the exploration space in initial phase. Afterwards individuals progress in a little range to regulate the trial solution to certain extent such that it can investigate reasonably little local space. Subsequently replicate the learning cycle over and over again.

The random number "r" is modified by

$$r' = \frac{1+random(0,1)}{2} \tag{17}$$

r'- Dynamic inertia weight. The mean value of the novel random number is amplified from 0.5 to 0.75, and then the stochastic variations are augmented. Mainly difference value added to the current learners. In the meantime, ω_c augment from little to big in single learning cycle. Underneath of joint outcome of ω_c , r' the projected algorithm will not engender premature convergence. It will perk up population diversity, shun prematurity in the exploration procedure and augment the capability of the fundamental TLBO to flee from local optima.

In teaching phase new-fangled set of enhanced learners are defined by,

$$X_{i,j}^{new} = \omega_c X_{i,j}^{old} + r'\left(X_{Teacher,j} - Te_F E^g\right) \tag{18}$$

In learner stage, the new-fangled set of enhanced learners is defined by,

$$X_{i,j}^{new} = \begin{cases} \omega_c X_{i,j}^{old} + r'\left(X_{i,j} - X_{q,j}\right) if\ f(X_i) < f(X_q) \\ \omega_c X_{i,j}^{old} + r'\left(X_{q,j} - X_{i,j}\right) \quad otherwise \end{cases} \tag{19}$$

Mutation procedure is very easy, and design variables are initialized arbitrarily in the exploration space:

$$P_c = 0.5exp\left(\frac{-iteration^2}{2\times(maximum\ iteration/8)^2}\right) \tag{20}$$

Step a: parameters are initialized
Step b: population generated
Step c: non-linear inertia weight factor, dynamic inertia weight computed by $\omega_c = 1 - exp\left(\frac{-\left(mod(iter,T)\right)^2}{2\times(T/8)^2}\right) \times (1 - \omega_{c\ minimum}), T \leq maximum\ iteration$; $r' = \frac{1+random(0,1)}{2}$
Step d: individual with the most excellent fitness is chosen and average value is computed
Step e: new marks of the learners are computed by $X_{i,j}^{new} = \omega_c X_{i,j}^{old} + r'\left(X_{Teacher,j} - Te_F E^g\right)$ and modernize the old values of the individuals by $Xnew_{(i)}^{g} = X_{(i)}^{g} + random \times \left(X_{Teacher}^{g} - Te_F E^g\right)$
Step f: compute the new-fangled values of the students; $X_{i,j}^{new} = \begin{cases} \omega_c X_{i,j}^{old} + r'\left(X_{i,j} - X_{q,j}\right) if\ f(X_i) < f(X_q) \\ \omega_c X_{i,j}^{old} + r'\left(X_{q,j} - X_{i,j}\right) \quad otherwise \end{cases}$ and modernize the old values of the individuals by $Xnew_{(i)}^{g} = X_{(i)}^{g} + random \times \left(X_{Teacher}^{g} - Te_F E^g\right)$
Step g: Compute probability of variation by $P_c = 0.5exp\left(\frac{-iteration^2}{2\times(maximum\ iteration/8)^2}\right)$
Step h: If the end condition is reached then stop or else go to Step c.

4. SIMULATION RESULTS

At first in standard IEEE 14 bus system [18] the validity of the proposed Advanced Teaching-Learning-Based Optimization algorithm (ATLBO) has been tested, Table 1 shows the constraints of control variables Table 2 shows the limits of reactive power generators and comparison results are presented in Table 3. Then the proposed ATLBO has been tested, in IEEE 30 Bus system. Table 4 shows the constraints of control variables, Table 5 shows the limits of reactive power generators and comparison results are presented in Table 6.

Table 1. Constraints of control variables

System	Variables	Minimum (PU)	Maximum (PU)
IEEE 14 Bus	Generator Voltage	0.95	1.1
	Transformer Tap	o.9	1.1
	VAR Source	0	0.20

Table 2. Constrains of reactive power generators

System	Variables	Q Minimum (PU)	Q Maximum (PU)
IEEE 14 Bus	1	0	10
	2	-40	50
	3	0	40
	6	-6	24
	8	-6	24

Table 3. Simulation results of IEEE −14 system

Control variables	Base case	MPSO [19]	PSO [19]	EP [19]	SARGA [19]	ATLBO
$VG-1$	1.060	1.100	1.100	NR*	NR*	1.017
$VG-2$	1.045	1.085	1.086	1.029	1.060	1.010
$VG-3$	1.010	1.055	1.056	1.016	1.036	1.016
$VG-6$	1.070	1.069	1.067	1.097	1.099	1.009
$VG-8$	1.090	1.074	1.060	1.053	1.078	1.020
Tap 8	0.978	1.018	1.019	1.04	0.95	0.919
Tap 9	0.969	0.975	0.988	0.94	0.95	0.917
Tap 10	0.932	1.024	1.008	1.03	0.96	0.920
$QC-9$	0.19	14.64	0.185	0.18	0.06	0.123
PG	272.39	271.32	271.32	NR*	NR*	271.82
QG (Mvar)	82.44	75.79	76.79	NR*	NR*	75.83
Reduction in PLoss (%)	0	9.2	9.1	1.5	2.5	26.18
Total PLoss (Mw)	13.550	12.293	12.315	13.346	13.216	10.002

NR* - Not reported.

Table 4. Constraints of control variables

System	Variables	Minimum (PU)	Maximum (PU)
IEEE 30 Bus	Generator Voltage	0.95	1.1
	Transformer tap	o.9	1.1
	VAR source	0	0.20

Table 5. Constrains of reactive power generators

System	Variables	Q Minimum (PU)	Q Maximum (PU)
IEEE 30 Bus	1	0	10
	2	-40	50
	5	-40	40
	8	-10	40
	11	-6	24
	13	-6	24

Table 6. Simulation results of IEEE −30 system

Control variables	Base case	MPSO [19]	PSO [19]	EP [19]	SARGA [19]	ATLBO
$VG-1$	1.060	1.101	1.100	NR*	NR*	1.010
$VG-2$	1.045	1.086	1.072	1.097	1.094	1.019
$VG-5$	1.010	1.047	1.038	1.049	1.053	1.012
$VG-8$	1.010	1.057	1.048	1.033	1.059	1.020
$VG-12$	1.082	1.048	1.058	1.092	1.099	1.026
VG-13	1.071	1.068	1.080	1.091	1.099	1.020
Tap11	0.978	0.983	0.987	1.01	0.99	0.929
Tap12	0.969	1.023	1.015	1.03	1.03	0.923
Tap15	0.932	1.020	1.020	1.07	0.98	0.920
Tap36	0.968	0.988	1.012	0.99	0.96	0.930
QC10	0.19	0.077	0.077	0.19	0.19	0.090
QC24	0.043	0.119	0.128	0.04	0.04	0.120
PG (MW)	300.9	299.54	299.54	NR*	NR*	297.54
QG (Mvar)	133.9	130.83	130.94	NR*	NR*	131.25
Reduction in PLoss (%)	0	8.4	7.4	6.6	8.3	20.11
Total PLoss (Mw)	17.55	16.07	16.25	16.38	16.09	14.020

5. CONCLUSION

In this paper Advanced Teaching-Learning-Based Optimization algorithm (ATLBO) successfully solved the optimal reactive power problem. In order to control the learner's mutation arbitrarily during the learning procedure a non-linear mutation factor has been applied. Preceding information gathering of learners is determined by the weight factor ω_c and through that new-fangled values are calculated. In a learning cycle individuals explored various regions of the exploration space in initial phase. Proposed Advanced Teaching-Learning-Based Optimization algorithm (ATLBO) has been tested in standard IEEE 14, 30 bus test systems and simulation results show the projected algorithm reduced the real power loss. Percentage of real power loss reduction has been improved when compared to other standard algorithms.

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