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ORIGINAL ARTICLE

Optimal setting of TCSCs in power systems using teaching–learning-based optimisation algorithm

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Abstract Teaching–learning-based optimisation (TLBO) is an emerging gradient-free optimisation algorithm inspired by interactions between students and teacher in classrooms. TLBO has no control parameter to be tuned by user. This property makes it popular in research community. It has been successfully applied to challenging optimisation problems in different areas. In this study, TLBO is assisted to find optimal setting of thyristor-controlled series compensators in electric power systems. The experiments have been done for both N-1 and N-2 line outage contingencies. The results show that TLBO performs well in solving this problem.

Keywords Teaching–learning-based optimisation · FACTS allocation problem · Contingency

1 Introduction

Using flexible AC transmission system (FACTS) devices is a very efficient and effective way for upgrading prevailing electric transmission systems [1–3]. They control the characteristics of power system and play a very sensitive role in power system control [4]. However, when such expensive devices are intended to be utilised in a power system, their optimal number/setting/location should be determined [5, 6]. This problem is referred to as FACTS allocation problem and is very difficult to be solved. For solving such a difficult optimisation problem, the best way is using heuristic algorithms. Heuristic algorithms are very flexible, i.e. do not entail the convexity, differentiability or continuity of objective functions [7–11]. Despite their undeniable merits, there are two issues in application of heuristics to FACTS allocation problems. First issue is that they generally suffer from premature convergence, i.e. they frequently converge into local optima rather than global one [12, 13]. This is due to lack of enough diversity among their search agents. The second issue is that heuristic algorithms have some control parameters. The computational behaviour of heuristics is highly dependent on their control parameters [14]. Control parameters should be tuned by user, while their tuning needs expertise.

In this study, teaching–learning-based optimisation (TLBO) is applied to FACTS allocation problem to address the two aforementioned issues. In TLBO, there is an appropriate diversity among search agents; therefore, its premature convergence probability is lower in comparison with some other heuristic algorithms. In addition, TLBO has no control parameter to be tuned by user. Due to the two mentioned reasons, TLBO seems to be a promising optimisation algorithm for solving FACTS allocation problems. It has been successfully applied to different optimisation problems in various areas [15–23]. The objective of this study is to utilise potential of TLBO in solving FACTS allocation problem. Thyristor-controlled series compensators (TCSCs) are used as FACTS devices.

The remainder of the paper is organised as follows; in Sect. 2, an overview of TLBO is provided. In Sect. 3, the proposed methodology is described. The results will be presented in Sect. 4. Finally, the conclusions are provided in Sect. 5.

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2 Overview of TLBO

This algorithm takes inspiration from teaching–learning interaction in a classroom and is developed by Rao [24]. It embraces a population of students in a class. In TLBO, different decision variables are analogous to different subjects offered to students and students' marks are analogous to fitness values in optimisation problems. The best student serves as the teacher, which is equivalent to swarm leader in particle swarm optimisation. In TLBO, the students learn in two ways: leaning from the teacher and learning from peers that are cleverer than themselves. Actually, TLBO embraces two phases: teaching phase wherein students learn from the teacher and student phase wherein students learn from their peers [24]. The main advantage of TLBO is that it is parameter free. There is no need to tune any control parameter in TLBO (other than class size and stopping criterion). Below, TLBO's two phases are described.

3 Teaching phase

In TLBO, at each iteration, the mean of decision vectors is computed and denoted by M, the student with the best mark is designated as teacher, and then, position of all students is updated via following equation [25]:

$$X_{i,\text{new}} = X_{i,\text{old}} + r(X_{\text{teacher}} - T_F.M) \tag{1}$$

T_F may be either 1 or 2 with equal probability, and X_{teacher} is the position of the teacher. $X_{i,\text{new}}$ and $X_{i,\text{old}}$ are, respectively, the new and old positions of student i. Symbol r denotes a random in [0, 1].

According to Eq. (1), the students are attracted towards the teacher, so their fitness values (marks) are enhanced.

3.1 Student phase

As in a real classroom, students learn from each other by discussions, presentations and formal communications; in student phase, for each student i, another student j is randomly picked up, and then, the student with better mark (fitness) is attracted towards (learns from) the other student. That is, if student j is fitter than student i, then

$$X_{i,\text{new}} = X_{i,\text{old}} + r_i\left(X_j - X_{i,\text{old}}\right) \tag{2}$$

Otherwise, if student j is fitter than i, the indices i and j in (2) are exchanged [25]. Then, if the new position has better fitness, the old position is replaced by the new one.

In TLBO, unlike most other heuristics, the number of fitness evaluations is computed as below.

$$NFE = (1 + 2N_P).t_{\max} \tag{3}$$

where N_P represents population size and t_{max} is maximum number of iterations.

Equation (3) shows that at each iteration, for each individual, the objective values are computed for two times, not one time. The flowchart of TLBO has been depicted in Fig. 1.

4 Methodology

The allocation of TCSCs is formulated as a multi-objective optimisation problem with three objectives [5]. The first objective is to minimise overloads in transmission lines. Its corresponding metric is calculated by Eq. (4).

$$OL = \sqrt{\sum_{i=1\ (for\ p_i > p_{i\max})}^{i=N_l} (p_i - p_{i\max})^2} \tag{4}$$

where P_i and $P_{i\max}$ represent the power flow and power flow limit of ith transmission line, respectively, and N_l is total number of branches in the system.

The second objective is to minimise voltage deviations of buses and is defined by Eqs. (5) and (6).

$$\text{DEV}_i = \begin{cases} 0 & \text{if } 0.95 \le V_i \le 1.05 \\ (1 - V_i)^2 & \text{if } 0.9 \le V_i \le .95\text{or}1.05 \le V_i \le 1.1 \\ \text{Inf} & \text{if } \ V_i > 1.1\text{or } V_i < 0.9 \end{cases} \tag{5}$$

where V_i represents the voltage of ith bus of power system.

$$\text{DEV} = \sum_{i=1 i \notin PV\text{buses}}^{i=N_B} \text{DEV}_i \tag{6}$$

The symbol N_B represents total number of buses in the power system.

It should be noted that in (6), voltage-controlled (PV) buses are excluded, since their voltages cannot be controlled by FACTS devices.

The third objective is to minimise losses of power system.

All the objectives are normalised with respect to their preoptimisation value, and their corresponding normalised objectives are represented by $J1$, J_2, J_3, respectively.

Linear weighted sum approach is used to transform the multi-objective problem into a single-objective problem as (7).

$$J = \omega_1 J_1 + \omega_2 J_2 + \omega_3 J_3 \tag{7}$$

It should be noted that in this study, TCSC is modelled as Fig. 2.

The simulations will be done on IEEE 14 bus power system [26]. First, contingency ranking is done based on overload values at different cases (case i means the

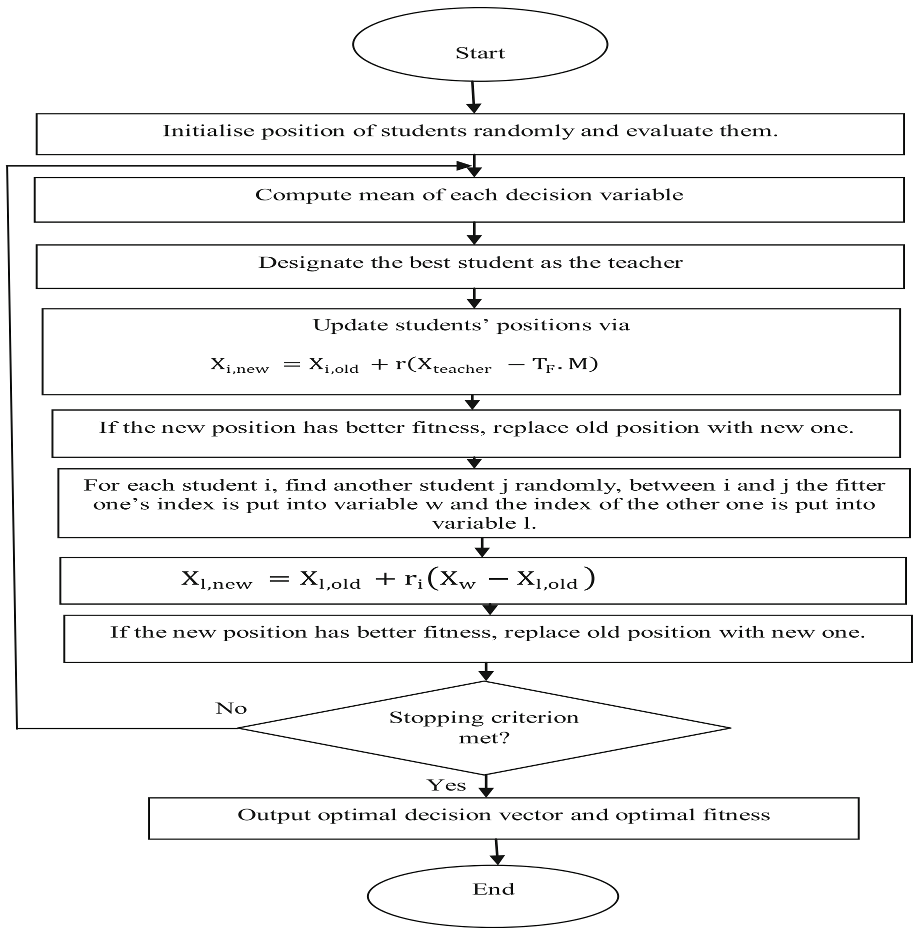

Fig. 1 Flowchart of TLBO

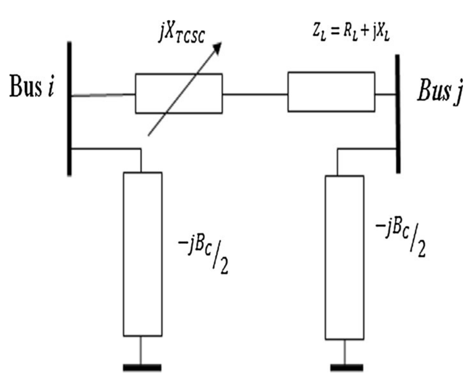

Fig. 2 Model of TCSC [4]

outage of line i). Consequently, cases 1, 2, 3 and 10 are the 4 most severe cases. Case 1 means outage of line 1, which connects bus 1 to bus 2; case 2 means outage of line 2, which connects bus 1 to bus 5; case 3 means outage of line 3, which connects bus 2 to bus 3; and case 10 means outage of line 10 which connects bus 5 to bus 6. TLBO and four other optimisation algorithms are applied to TCSC allocation problem for N-1 line outage contingencies (cases 1, 2, 3 and 10) and N-2 line outage contingencies. All algorithms are run for 30 times.

The coefficients in multi-objective framework are selected as follows:

$$\omega_1 = 0.5, \omega_2 = 0.3, \omega_3 = 0.2$$

The number of individuals for all algorithms except TLBO is set to 300, and maximum number of iterations is 100, that is, the number of function evaluations is 30,300. In TLBO, since the number of function evaluations at each iteration is different from other heuristic algorithms, it is terminated when the number of function evaluations reaches 30,300. In this way, all algorithms are fairly compared with the same number of function evaluations. The steps of employing TLBO for finding optimal setting of TCSCs are as follows.

1. Data of power system including bus data, branch data, power flow limits and case number are entered. The maximum allowable active power of each branch is computed as 1.2 times of its active power prior to contingency.
2. All students are initialised in feasible region of search space. Each student is a set of TCSC reactances, where its ith dimension represents

reactance of the TCSC unit inserted in ith branch. The reactance of ith TCSC is bounded in $[-2X_{Li}, 2X_{Li}]$, where X_{Li} represents the reactance of ith branch

3. The mean of each decision variable is computed, and the best student is chosen as the teacher.
4. The positions of students are updated via Eq. (1).
5. Newton–Raphson power flow is applied, and objective value (J) is computed for each student.
6. For each student, if the objective value at its new position is lower than the objective value at current position, its position is changed to the new position.
7. For each student i, another student j is randomly selected and Eq. (2) is applied.
8. Newton–Raphson power flow is applied, and objective value for each student is computed
9. For each student, if the objective value at its new position is lower than the objective value at current position, its position is changed to the new position.
10. Steps 3–9 are iterated until termination criterion is met.
11. Optimal reactance of TCSCs and optimal values for OL, DEV, P_{loss} and J are displayed.
12. End

5 Results and discussion

5.1 Results for N-1 line outage contingencies

5.1.1 Results for the most severe case (case 1)

This section validates the superior performance of TLBO in finding optimal setting of TCSC devices. In Tables 1 and 2, the results for case 1 are presented. The best results are bolded.

According to Table 1, TLBO lowers overall objective by 94.89 %. In terms of mean of overall objectives, TLBO performs better than other optimisation algorithms. The standard deviation of objectives delivered by TLBO is lower than standard deviations achieved by other heuristic algorithms. This signifies high stability of TLBO in finding quality solutions.

Table 2 shows the average of different objectives for case 1 achieved by different algorithms. The table indicates that TLBO lowers overloads by 99.17 %. It also indicates that in terms of overload minimisation, TLBO performs better than all other algorithms. For instance, the overload in TLBO shows 97.86 % improvement with respect to GSA. In terms of voltage deviations, TLBO along with NLP functions better than other optimisation algorithms. Actually, they remove all voltage deviations in buses. Ultimately, in terms of minimising power losses, TLBO delivers low values and outperform all other algorithms. The power loss of the system by TLBO has been lowered 76.53 % with respect to preoptimisation state.

Table 1 Monte Carlo numerical results in case 1

	NLP [27]	PS [28]	GSA [29]	FSO [30]	TLBO
Mean	0.6664	0.3509	0.4606	0.1185	**0.0511**
Std	0	0	0.1074	0.0659	0.0310
Min	0.6664	0.3509	0.3175	0.0295	**0.0215**
Max	0.6664	0.3509	0.5971	0.2869	**0.1207**

The best results are in bold

5.1.2 Results for the second most severe contingency (case 2)

The results for case 2 are tabulated in Tables 3 and 4. Table 3 implies that in terms of mean of overall objectives, TLBO functions better than all other optimisation algorithms. In addition, the standard deviation of objectives achieved by TLBO in case 2 is lower than those achieved by other heuristic algorithms, which approves high stability of TLBO in finding accurate solutions.

Table 4 tabulates the mean of different objectives for case 2 acquired by different algorithms. Table 4 signifies that in terms of overload minimisation, TLBO outperforms all other algorithms. For instance, the overload in TLBO shows 98.40 % improvement with respect to GSA. In terms of voltage deviations, TLBO along with NLP and PS return very low values and outshines all other optimisation algorithms. Eventually, in terms of minimising power losses, TLBO results in the lowest value and outranks other algorithms.

Table 2 Comparison of different algorithms for case 1

Objective	Preoptimisation	NLP	PS	GSA	FSO	TLBO
OL	1.7420	1.6621	0.4963	0.6729	0.1041	**0.0144**
DEV	0.0086	0	0.0040	0.0046	0.0011	**0**
P_{loss}	0.4197	0.3974	0.1432	0.2233	0.1023	**0.0985**
J	1	0.6664	0.3509	0.4606	0.1185	**0.0511**

The best results are in bold

Table 3 Monte Carlo numerical results in case 2

	NLP	PS	GSA	FSO	TLBO
Mean	0.6855	0.3083	0.4204	0.1855	**0.0647**
Std	0	0	0.1728	0.0720	0.0303
Min	0.6855	0.3083	0.2162	0.0418	**0.0277**
Max	0.6855	0.3083	0.5463	0.3281	**0.1387**

The best results are in bold

Table 4 Comparison of different algorithms for case 2

Objective	Preoptimisation	NLP	PS	GSA	FSO	TLBO
OL	0.8248	0.8069	0.3180	0.3194	0.0927	**0.0051**
DEV	0.0122	**0**	**0**	0.0029	0.0015	3.3615e-4
P_{loss}	0.2100	0.2061	0.1213	0.1631	0.0981	**0.0560**
J	1	0.6855	0.3083	0.4204	0.1855	**0.0647**

The best results are in bold

Table 5 Monte Carlo numerical results in case 3

	NLP	PS	GSA	FSO	TLBO
Mean	0.6823	0.6816	0.3838	0.1957	**0.0425**
Std	0	0	0.3025	0.1969	0.0148
Min	0.6823	0.6816	0.1045	0.0372	**0.0287**
Max	0.6823	0.6816	0.6455	0.6853	**0.0718**

The best results are in bold

Table 6 Comparison of different algorithms for case 3

Objective	Preoptimisation	NLP	PS	GSA	FSO	TLBO
OL	0.8108	0.7889	0.7876	0.2630	0.1264	**0**
DEV	0.0122	0	0	0.0040	0.0013	**0**
P_{loss}	0.2474	0.2422	0.2424	0.1534	0.1066	**0.0526**
J	1	0.6823	0.6816	0.3838	0.1957	**0.0425**

The best results are in bold

5.1.3 Results for the third most severe case (case 3)

The results for case 3 are tabulated in Tables 5 and 6. Table 6 shows that in terms of mean of overall objectives, TLBO outshines all other optimisation algorithms and improves overall objective by 95.75 % with respect to preoptimisation state. The standard deviation of objectives achieved by TLBO in case 3 is very lower than standard deviations achieved by other heuristic algorithms, which again approves high stability of TLBO.

Table 6 tabulates the mean of different objectives for case 3 achieved by different algorithms. It indicates that in minimisation of overload/voltage deviation/losses, TLBO significantly outperforms all other algorithms.

5.1.4 Results for the fourth most severe contingency (case 10)

The results for case 10 are tabulated in Tables 7 and 8. Table 7 signifies that in terms of mean of overall objectives, in case 10, TLBO behaves better than other optimisation techniques.

Table 8 displays the mean of all objectives for case 10. It indicates that in overload minimisation, TLBO outdoes all other algorithms. For instance, the overload in TLBO shows 18.76 % decrease with respect to GSA. In terms of voltage deviations, TLBO along with PS deliver very low values and outdo other algorithms. Ultimately, in terms of minimising power losses, TLBO returns the least values and outdoes all other algorithms.

5.2 Results for N-2 line outage contingencies

In this section, the performance of TLBO and other optimisation algorithms in handling N-2 contingencies is evaluated. The problem is formulated the same as that explained in Sect. 3. N-2 contingencies are considered as very severe contingencies and can cause severe problems and consequences in power systems. Three severe N-2 line outage contingencies are selected. The results achieved by different optimisation algorithms for different contingencies have been tabulated in Tables 9, 10, 11, 12, 13, 14. The tables obviously show that in all selected N-2 line outage contingencies, TLBO behaves better than other used

Table 7 Monte Carlo numerical results in case 10

	NLP	PS	GSA	FSO	TLBO
Mean	0.6788	0.5918	0.5898	0.4999	**0.3344**
Std	0	0	0.1992	0.0878	0.0930
Min	0.6788	0.5918	0.4490	0.3272	**0.2562**
Max	0.6788	0.5918	0.7307	0.6060	**0.5751**

The best results are in bold

Table 8 Comparison of different algorithms for case 10

Objective	Preoptimisation	NLP	PS	GSA	FSO	TLBO
OL	0.3360	0.2724	0.2633	0.1642	0.1885	**0.1334**
DEV	0.0223	0.0055	**0**	0.0127	0.0069	0.0018
P_{loss}	0.1668	0.1668	0.1668	0.1453	0.1059	**0.0926**
J	1	0.6788	0.5918	0.5898	0.4999	**0.3344**

The best results are in bold

Table 9 Monte Carlo numerical results for outage of lines 1 and 3

	NLP	PS	GSA	FSO	TLBO
Mean	0.66172	0.4449	0.4209	0.1921	**0.0670**
Std	0	0	0.2055	0.1070	0.0607
Min	0.66172	0.4449	0.1949	0.0190	**0.0170**
Max	0.66172	0.4449	0.6034	0.3210	**0.1508**

The best results are in bold

Table 10 Comparison of different algorithms for outage of lines 1 and 3

Objective	Preoptimisation	NLP	PS	GSA	FSO	TLBO
OL	2.0083	1.8868	1.2248	0.3895	0.3994	**0.1130**
DEV	0.0082	0	0	0.0066	7.5859e-4	**0**
P_{loss}	0.5004	0.4803	0.3502	0.2087	0.1623	**0.0973**
J	1	0.66172	0.4449	0.4209	0.1921	**0.0670**

The best results are in bold

Table 11 Monte Carlo numerical results for outage of lines 1 and 10

	NLP	PS	GSA	FSO	TLBO
Mean	0.66403	0.1656	0.6207	0.1820	**0.1213**
Std	0	0	0.1813	0.1070	0.0197
Min	0.66403	0.1656	0.4776	0.1037	**0.0926**
Max	0.66403	0.1656	0.8864	0.4044	**0.1448**

The best results are in bold

Table 12 Comparison of different algorithms for outage of lines 1 and 10

Objective	Preoptimisation	NLP	PS	GSA	FSO	TLBO
OL	2.0043	1.8838	0.4136	1.3854	0.2662	**0.2496**
DEV	0.0181	**0**	**0**	0.0071	0.0036	4.4512e-4
P_{loss}	0.4863	0.4719	0.1518	0.3814	0.1375	**0.1257**
J	1	0.66403	0.1656	0.6207	0.1820	**0.1213**

The best results are in bold

Table 13 Monte Carlo numerical results for outage of lines 2 and 3

	NLP	PS	GSA	FSO	TLBO
Mean	0.6904	0.6909	0.5572	0.2065	**0.0417**
Std	0	0	0.2034	0.1552	0.0405
Min	0.6904	0.6909	0.3463	0.0550	**0.0214**
Max	0.6904	0.6909	0.7522	0.5486	**0.1243**

The best results are in bold

Table 14 Comparison of different algorithms for outage of lines 2 and 3

Objective	Preoptimisation	NLP	PS	GSA	FSO	TLBO
OL	1.5435	1.5322	1.5327	0.7699	0.2009	**0.0036**
DEV	0.0085	**0**	**0**	0.0055	0.0025	5.0795e-4
P_{loss}	0.3943	0.3826	0.3832	0.2237	0.1055	**0.0447**
J	1	0.6904	0.6909	0.5572	0.2065	**0.0417**

The best results are in bold

optimisation algorithms. For instance, for outage of lines 1 and 3, TLBO leads to a low value of overload metric, removes all voltage deviations and results in low value of losses.

6 Conclusions

TLBO has been assisted to find optimal setting of TCSCs in a power system during both N-1 and N-2 contingencies. The results vividly show that TLBO is efficient in solving this problem, since it drastically decreases overloads, voltage deviations and power losses. TLBO offers lower overloads, voltage deviations and power losses than four states of the art optimisation algorithms including gravitational search algorithm (GSA), nonlinear programming (NLP), pattern search (PS) and firefly swarm optimisation (FSO). As a direction for future research, application of TLBO for finding optimal location and setting of other FACTS devices such as unified power flow controller, interline power flow controller and static synchronous series compensator is recommended.

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