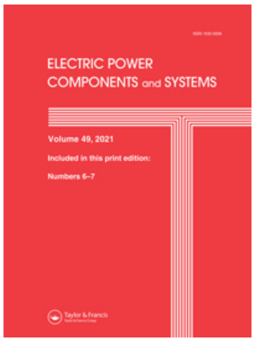

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Optimal Power Flow via Teaching-Learning-Studying-Based Optimization Algorithm

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CONTENTS

Abstract—The teaching-learning-based optimizer (TLBO) algorithm is a powerful and efficient optimization algorithm. However it is prone to getting stuck in local optima. In order to improve the global optimization performance of TLBO, this study proposes a modified version of TLBO, called teaching-learning-studying-based optimizer (TLSBO). The proposed enhancement is based on adding a new strategy to TLBO, named studying strategy, in which each member uses the information from another randomly selected individual for improving its position. TLSBO is then used for solving different standard real-parameter benchmark functions and also various types of nonlinear optimal power flow (OPF) problems, whose results prove that TLSBO has faster convergence, higher quality for final optimal solution, and more power for escaping from convergence to local optima compared to original TLBO.

1. INTRODUCTION

In the last few years, population-based swarm intelligence based on various evolutionary algorithms (EAs) has been a great research interest to many researchers in the various fields needing optimal solutions of problems, for example for the optimal solutions of various types of engineering optimization problems in the engineering systems. Therefore, various heuristic techniques and evolutionary algorithms are required for solving and finding optimum solutions of engineering optimization problems effectively and in an acceptable manner. General-purpose optimization methods, like particle swarm optimization (PSO) algorithm [1], Turbulent Flow of Water-based Optimization [2], differential evolution (DE) algorithm [3], artificial bee colony (ABC) [4], teaching-learning-based optimization (TLBO) [5] were proposed in the literature which are capable of finding efficient and acceptable optimal or near-optimal solutions for many engineering and real-world optimization

Keywords: TLBO algorithm, TLSBO, studying strategy, real-parameter benchmark functions, power system optimization problems, optimal power flow, optimization
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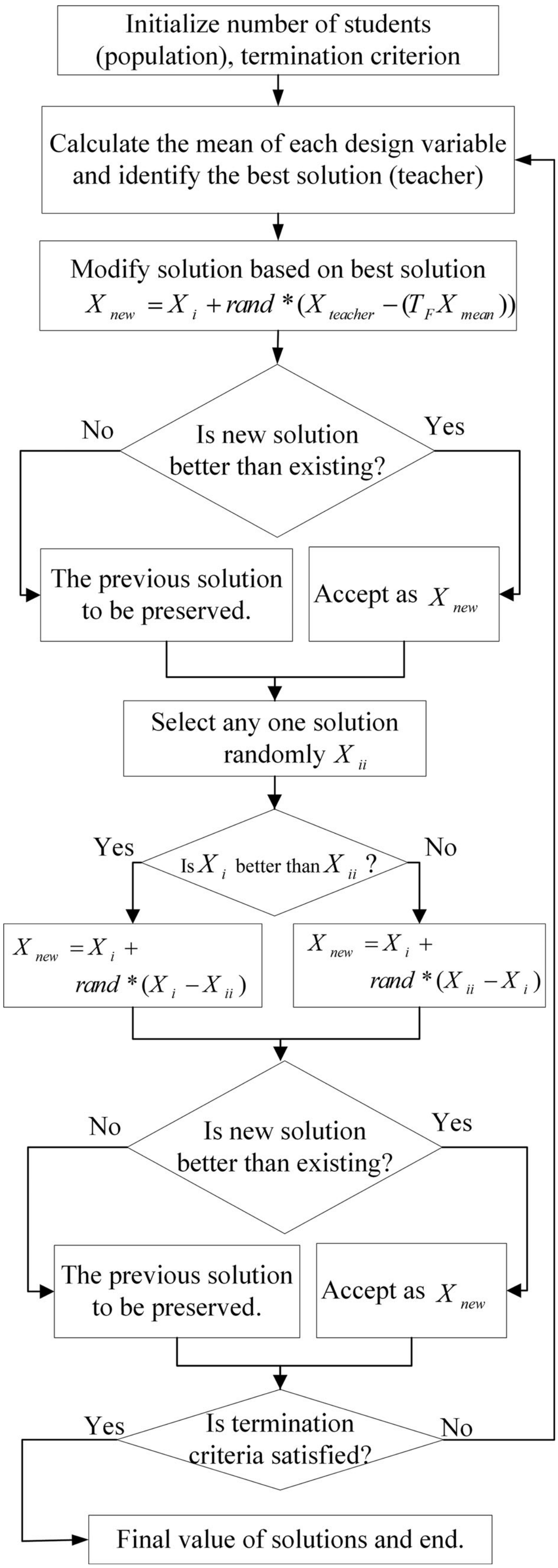

FIGURE 1. The optimization process of the original TLBO algorithm.

problems having many nonlinear characteristics in the acceptable and fast simulation time. Moreover, classical optimization methods are not efficient and acceptable in solving most engineering and real-world optimization since they compute only local optima [6].

The OPF problem, as a major problem in power system operations, has been solved using many classical optimization methods such as Newton-based techniques, Quadratic Programming, Interior Point Methods, Linear Programming, and Non-Linear Programming [7]. However, these methods face difficulties in handling non-convex and/or non-smooth problems. Furthermore, they are slow in solving large-scale problems and may be stuck in local optima. Therefore, in recent years, the nature-inspired metaheuristic optimization algorithms have widely been used for solving the OPF problems. This paper proposes and develops a new and efficient strategy into original TLBO algorithm for solving different types of nonlinear optimal power flow (OPF) problems in the power system. TLBO [5, 8] is a parameter-free and simple algorithm which has good feasibility and performance in solving different engineering optimization problems [6] like: the distribution system state estimation [9], improved mutagenic primer design [10], parameters optimization of selected casting processes [8], the design of space trusses [11], the dynamic economic emission dispatch (DEED) [12], the energy loss minimization [13], optimization of multi-level production in petrochemical industry [14], the control DVR compensator [15], flexible job-shop scheduling [16], the parameters identification of PEM fuel cell and solar cell models [17], etc.

TLBO is one of the most successful metaheuristic optimization algorithms and many researches focused on improving its performance by different strategies; some of them include interactive teaching-learning optimizer (ITLO) for optimal tuning of VSC-HVDC systems [18], TLBO algorithm with dynamic group strategy [19], an adaptive inertia weight TLBO [20], an improved TLBO for parameter extraction of photovoltaic models [21], hybrid TLBO and neural network algorithm [22], A chaotic TLBO [23], and dynamic opposite learning enhanced [24]. In this paper, a novel strategy is proposed for TLBO that improves its performance and helps it in escaping from convergence to local optima.

The rest of the article is organized as follows: in Sec. 2 the formulation of the original TLBO is explained and the proposed strategy is introduced. The first part of simulation study is presented in Sec. 3, in which the optimization results of standard real-parameter test functions are compared for different algorithms. In the second part of

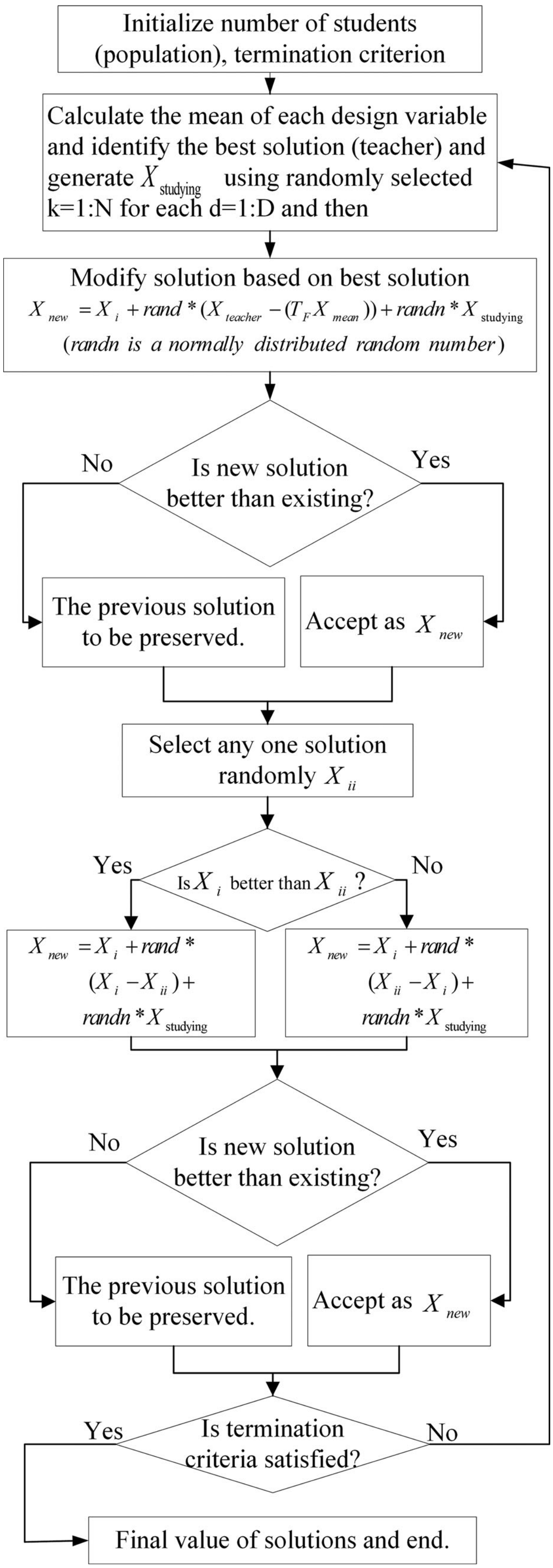

FIGURE 2. The optimization process of TLSBO.

simulation study, in Sec. 4, TLSBO algorithm is used for solving power system OPF optimization problems. Finally, in Sec. 5 some conclusions of the paper are given.

2. TLBO ALGORITHM

TLBO algorithm [5, 6] is an effective and efficient algorithm based on the influence of a teacher on learners in a classroom; learners are considered as population and design variables are considered as offered courses. The optimization process flowchart for the basic TLBO algorithm is given in Figure 1. The original TLBO is consisted of two phases: teaching phase and learning phase [5], which is described in the following subsections:

2.1. Teaching Phase

The teacher is considered as the person with the most experimental information and knowledgeable (the best solution obtained in all population of TLBO). During the first phase of TLBO, the teacher ($X_{teacher}$) makes an effort to improve the mean of the classroom (X_{mean}) up to his/her level. The teaching phase for the member or student ith of the population (X_i) is formulated as follows [5]:

$$X_{new} = X_i + r(X_{teacher} - (T_F X_{mean})) \tag{1}$$

where the learning changing factor T_F is determined randomly as $T_F = round[1 + rand(0, 1)]$, and also, the index r is a random value between 0 and 1.

2.2. Learning Phase

Students improve their experimental information and knowledge in the teaching phase and by interaction between themselves, where the latter phase is called the learning phase [5]. In the learning phase, student ith (X_i) makes an effort to improve his/her experimental information and knowledge by learning from another random student X_{ii} of the classroom, where value ii must be different from value i. Depending on the objective function values of solutions X_i and X_{ii}, two possibilities can occur: if X_{ii} is better than X_i (for minimization problems: $f(X_{ii}) \leq f(X_i)$), X_i is moved toward X_{ii} according to Eq. (2). Otherwise ($f(X_i) < f(X_{ii})$), it is moved away from X_{ii} according to Eq. (3). If obtained new student or new solution X_{new} according to Eq. (2) or (3), has better objective function value (for minimization problems: $f(X_{new}) \leq f(X_i)$), he/she will be accepted into the algorithm population. The learning phase for the member or student ith of the population (X_i) can be achieved as follows [5]:

f		Index	GL-25	DE/rand/2	CLPSO	TLBO	TLSBO
Uni-modal Func.	f_1	Mean	3.230E − 26	3.718E − 08	1.855E − 13	7.405E − 24	**4.880e−028**
		Std.	5.146E − 26	3.560E − 09	2.201E − 13	3.534E − 22	9.931e − 028
		Best	1.262E − 29	3.017E − 09	1.007E − 13	8.338E − 28	0.000E + 00
		Rank	2	5	4	3	1
	f_2	Mean	1.853E + 02	6.827E + 03	3.894E + 03	3.519E + 00	**4.688E−05**
		Std.	2.406E + 02	1.938E + 03	6.900E + 02	1.925E + 01	4.930E − 05
		Best	4.300E − 02	4.478E + 03	1.045E + 03	2.188E − 05	1.671E − 06
		Rank	3	5	4	2	1
	f_3	Mean	3.850E + 06	9.105E + 07	2.382E + 07	1.104E + 06	1.011E + 006
		Std.	2.519E+06	1.664E+07	8.402E+06	5.718E + 05	2.115E + 005
		Best	1.280E + 06	5.598E + 07	1.263E + 07	5.124E + 05	4.612E + 005
		Rank	3	5	4	2	1
	f_4	Mean	1.992E + 03	1.223E + 04	1.312E + 04	2.407E + 03	**2.271E+02**
		Std.	9.256E + 02	2.983E + 03	2.536E + 03	1.946E + 03	1.878E + 02
		Best	7.912E + 02	8.234E + 03	9.702E + 03	2.341E + 03	2.683E + 01
		Rank	2	4	5	3	1
	f_5	Mean	3.142E + 03	**1.629E+03**	4.405E + 03	4.219E + 03	3.044E + 03
		Std.	2.197E + 02	4.540E + 02	4.675E + 02	7.727E + 02	1.013E + 03
		Best	2.606E + 03	9.835E + 02	3.986E + 03	2.950E + 03	2.131E + 03
		Rank	3	1	5	4	2
Multi − modal Func.	f_6	Mean	3.739E + 01	2.443E + 01	**2.073E+01**	5.769E + 01	2.236E + 01
		Std.	2.525E + 01	7.620E − 01	1.169E + 01	4.852E + 01	3.110E + 01
		Best	6.625E + 00	2.317E + 01	3.271E + 00	1.918E + 00	1.839E − 02
		Rank	4	3	1	5	2
	f_7	Mean	4.477E − 02	5.884E − 01	1.115E + 00	1.778E − 01	**2.300E−02**
		Std.	3.712E − 02	1.365E − 01	5.902E − 02	4.161E − 01	1.850E − 02
		Best	5.061E − 03	3.439E − 01	1.034E + 00	1.542E − 05	2.463E − 10
		Rank	2	4	5	3	1
	f_8	Mean	2.099E + 01	2.098E + 01	2.099E + 01	2.098E + 01	**2.095E+01**
		Std.	5.460E − 02	3.986E − 02	4.293E − 02	4.393E − 02	1.689E − 02
		Best	2.082E + 01	2.088E + 01	2.086E + 01	2.096E + 01	2.078E + 01
		Rank	3	2	3	2	1
	f_9	Mean	2.844E + 01	1.578E + 02	**4.703E−06**	1.160E + 02	4.668E + 01
		Std.	6.883E + 00	8.063E + 00	5.507E − 06	2.229E + 01	1.373E + 01
		Best	1.618E + 01	1.375E + 02	5.392E − 07	7.861E + 01	2.620E + 01
		Rank	2	5	1	4	3
	f_{10}	Mean	1.443E + 02	2.593E + 02	1.323E + 02	1.530E + 02	**1.144E+02**
		Std.	6.120E + 01	1.342E + 01	2.100E + 01	2.900E + 01	4.009E + 01
		Best	3.520E + 01	1.742E + 02	9.146E + 01	7.886E + 01	2.619E + 01
		Rank	3	5	2	4	1
	f_{11}	Mean	3.625E + 01	3.976E + 01	**2.814E+01**	3.395E + 01	3.567E + 01
		Std.	6.761E + 00	1.610E + 00	1.450E + 00	2.660E + 00	1.200E + 00
		Best	1.654E + 01	3.674E + 01	2.465E + 01	3.012E + 01	3.409E + 01
		Rank	4	5	1	2	3
	f_{12}	Mean	1.156E + 04	3.334E + 05	3.242E + 04	7.500E + 05	**1.117E+04**
		Std.	9.393E + 03	5.984E + 04	8.592E + 03	1.700E + 05	1.862E + 04
		Best	2.038E + 03	1.812E + 05	1.547E + 04	1.586E + 05	7.276E + 02
		Rank	2	4	3	5	1
Nb/Nw/Mr			0/1/2.75	1/6/4.0	0/1/2.750	1/6/4.000	3/4/3.167

TABLE 1. The results obtained from the algorithms for real-parameter problems $FEs = 150{,}000$.

$$X_{new} = X_i + rand(X_{ii} - X_i), \qquad \text{if} \quad f(X_{ii}) \le f(X_i) \tag{2}$$
$$X_{new} = X_i + rand(X_i - X_{ii}), \qquad \text{if} \quad f(X_i) \le f(X_{ii}) \tag{3}$$

Also, infeasible new solutions must be properly handled, to decide that if one member or student is better than another student or not. The penalty method is used for constraint handling as in [5, 25].

2.3. Studying Phase (The Proposed Strategy)

There are many various complicated real-world problems, like engineering problems, etc., which have many local optimal solutions. In optimizing such problems using TLBO algorithm, if teacher member of TLBO is trapped in one of these local optimal solutions and fails to escape from it in the following iterations, according to Eq. (1), all population or students gradually moves toward this solution, and their position would get equal to the teacher member; so the global and local search equations, i.e. learning and teaching phases, gradually lose their effectiveness in optimization process and the algorithm would converge to the local optimum. Therefore, the algorithm requires a new optimization strategy or a suitable mutation to generate population diversity for such specific functions and conditions in order to continue optimization [26]. Here, for escaping the local optima and enhancing the power of the algorithm, a new appropriate strategy, called studying strategy, is proposed for TLBO algorithm, which is shown in Figure 2. In this phase, the ith member tries to change and improve its position by appropriately changing each dimension of its position.

$$X_{\text{studying},d} = \begin{cases} rand * (X_{k,d} - X_{i,d}), & \text{if } f(X_k) \le f(X_i) \\ rand * (X_{i,d} - X_{k,d}), & \text{if } f(X_i) < f(X_k) \end{cases}$$
$$d = 1:D, \text{ and the } k\text{th member is chosen randomly for each dimension}: k = 1:N \tag{4}$$

In (4), a new member k is selected for each dimension d. This strategy aggregated with teaching and learning phases, prevents converging to local optima and considerably increase the power of the algorithm. In this strategy, all the students are used for changing each dimension of each student; an appropriate combination which helps effectively to add variety to the population and escaping from local optima. In this way, good exploration is achieved while assuring exploitation. The pseudo code of studying strategy is shown below:

The pseudo code of studying strategy for the member ith of TLSBO:

for $d = 1{:}\ D$

$k = 1 + \text{round}(rand^*(N-1))$;

$$X_{\text{studying},d} = \begin{cases} rand * (X_{k,d} - X_{i,d}), & \text{if } f(X_k) \le f(X_i) \\ rand * (X_{i,d} - X_{k,d}), & \text{if } f(X_i) < f(X_k) \end{cases}$$

end

2.4. Multi-Objective Strategy into TLSBO

Multi-objective optimization problems (MOOP) are the problems having two or more objective functions (OFs) which must be optimized simultaneously. In this type of optimization problems the "best compromise" solution is being sought. In MOOP, the concept of Pareto optimality is used to assess the efficiency of the solutions with regard to each other. In a minimization problem, for each two solution X_1 and X_2, if we have $f_i(X_1) \le f_i(X_2)$ for all objective functions and $f_j(X_1) < f_j(X_2)$ for at least one objective function, it is said that the solution X_1 Pareto dominates the solution X_2. This can be mathematically shown as [25]:

$$\begin{array}{ll} \forall i \in \{1, \quad 2, \quad \dots \quad ,n\}, & f_i(X_1) \le f_i(X_2), \\ \exists j \in \{1, \quad 2, \quad \dots \quad ,n\}, & f_j(X_1) < f_j(X_2), \end{array} \tag{5}$$

where n is the number of objective functions. The solutions that cannot be Pareto dominated by any other solution are called Pareto optimal solutions and the set of the objective values of Pareto optimal solutions is called Pareto front. In the optimization process, the set of non-dominated solutions will be saved in a repository, iteratively.

Furthermore, a fuzzy method is employed here to handle the competing objective functions of the MOOP under consideration. In the fuzzy method a membership function (MF) is defined for each objective function f_i, as in (6).

$$\mu_{Fi}(X) = \begin{cases} 1 & , \quad f_i(X) \le F_i^{\min} \\ 0 & , \quad f_i(X) \ge F_i^{\max} \quad i = 1, 2, \dots, n \\ \dfrac{F_i^{\max} - f_i(X)}{F_i^{\max} - F_i^{\min}} & , \quad F_i^{\min} \le f_i(X) \le F_i^{\max} \end{cases} \tag{6}$$

where the values of $F_i^{\min}$ and $F_i^{\max}$ are calculated by means of the payoff table.

In order to compose the payoff table for a MOOP with p conflicting OFs, initially, the single objective function considering only one of the OFs is solved. Assume that F_j^i is the value of jth objective function for the optimal solution of the single-objective problem considering only ith objective function (so, $F_i^* = F_i^i$ is the optimal value of f_i). Then, the ith row of the payoff table will be $F_1^i, \dots, F_{i-1}^i, F_i^*, F_{i+1}^i, \dots, F_n^i$. When the explained approach is repeated for all objective functions, the payoff table is completely calculated. Then the

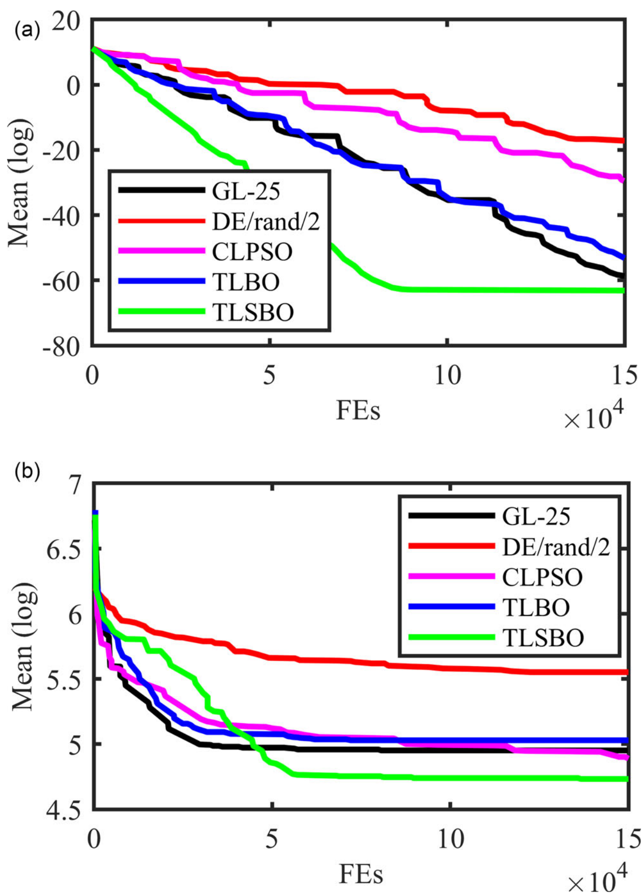

FIGURE 3. The convergence graphs of 30 runs of algorithms for (a) f_1 and (b) f_{10} functions.

minimum and maximum values among the values in the ith column of the payoff table are $F_i^{\min}$ and $F_i^{\max}$, respectively, which can be used in the fuzzy model. It should be noted that the above-mentioned membership functions are continuous and monotonic. The membership functions of the solutions in the non-dominated solutions repository are normalized using (7):

$$N_\mu(j) = \frac{\sum_{i=1}^{n} w_i \times \mu_{Fi}(X_j)}{\sum_{j=1}^{N_{rep}} \sum_{i=1}^{n} w_i \times \mu_{Fi}(X_j)} \tag{7}$$

where N_{rep} is the size of the repository and w_i is the weighing factor representing the decision maker priority over the ith objective function. This normalized MF is used for sorting the non-dominated solutions.

3. TLSBO ALGORITHM FOR REAL-PARAMETER PROBLEMS

In the first part of simulation study, in order to validate the performance of TLSBO algorithm for real-parameter optimization, various types of real-parameter functions are chosen [27] based the Mean (mean value of the best results), the Best (the best result in all runs), and Std (standard deviation of the best results), which are summarized in the Appendix. In this section of study, the characteristics including general performance, robustness and precision of GL-25 [28], DE/rand/2 [29], (F (scaling factor) = 0.45 and, CR (crossover factor) = 0.7), CLPSO [30], original TLBO and proposed TLSBO algorithms are compared using 12 real-parameter test functions, which are summarized in the [27]. The real-parameter test functions are multi-modal, non-separable, scalable test functions which have a very long, narrow and parabolic shaped valley from local minimum to global minimum, which make them very difficult to solve [27]. Each algorithm is run 30 times for each real-parameter test function and the results including the Mean, the Best, Std are presented in Table 1. In these simulations the population size is considered $N = 30$, the maximum value of function evaluations $FEs = 150{,}000$ and dimension $D = 30$. In this table, rank shows the order of the Mean indices of algorithms sorted increasingly, Nb is the number of times that this algorithm is better than other algorithms, Nw is the number of times that this algorithm is worse than other algorithms, and Mr is the mean of rank of the algorithm for all functions. According to the results, proposed TLSBO algorithm surpasses original TLBO and other algorithms on obtaining better final solution and less converging to local minimum. The results show that TLSBO algorithm has successfully solved different real-parameter optimization problems. The mean of convergence graphs of 30 runs of algorithms for f_1 and f_{10} test functions are shown in Figure 3.

In Table 2, different population sizes were tested for the proposed TLSBO algorithm. As observed, the population size between 30 and 60 can be an appropriate choice for functions with dimensions around 30. However, depending on the characteristics of the optimization functions in different problems, it is possible for a specific population size to reach a more optimal solution, which is the nature of all evolutionary algorithms.

4. TLSBO FOR THE OPF PROBLEMS

In the second part of simulation study, experiments were conducted to compare the results of the proposed TLSBO algorithm with other obtained optimal best results reported in the previous literature for solving the various static optimal electrical power generation and transmission planning problems. In an electric energy generation competitive environment, the

f	Index	Population size 15	45	60	30
f_3	Mean	9.766E+05	1.459E+06	1.498E+06	1.011E+006
	Std.	2.483E+05	5.551E+05	1.152E+06	2.115E+005
	Rank	1	3	4	2
f_5	Mean	3.598E+03	3.285E+03	3.105E+03	3.044E+03
	Std.	1.4460E+03	1.063E+03	1.103E+03	1.013E+03
	Rank	4	3	2	1
f_9	Mean	6.437E+01	3.358E+01	2.189E+01	4.668E+01
	Std.	1.414E+01	9.205E+00	1.200E+01	1.373E+01
	Rank	4	2	1	3
f_{12}	Mean	1.263E+04	1.317E+04	2.408E+03	1.117E+04
	Std.	2.074E+04	2.545E+04	2.194E+03	1.862E+04
	Rank	3	4	1	2

TABLE 2. The results obtained from TLSBO with different population sizes and $FEs = 150{,}000$.

static OPF problems are non-convex and non-linear optimization problems with both continuous and discrete decision variables. The original objective of the OPF problems is to optimize different non-linear objective functions subject to a set of constraints imposed by electrical power generation and transmission system limitations.

The formulation of the OPF problem and the best results obtained from TLSBO algorithm in comparison with previous reported results for the OPF problems for 30 runs are presented in the following sections.

4.1. The Optimal Power Flow (OPF) Problems

Generally, the aim of OPF problem is to optimize one or more objective functions by optimally adjusting power system control parameters subject to some equality and inequality constraints [31, 32]. Summary of some optimization algorithms used for the solution of different OPF problems in recent literature (since 2014) are decomposition-based algorithms [33], evolutionary algorithms (EA) [34], improved multi-objective ABC algorithm [35], multi-hive bee foraging algorithm (MHBFA) [35], modified TLBO [36], an improved adaptive DE [37], hybrid fuzzy PSO and Nedler–Mead algorithm (HFPSO-NM) [38], learning DE-APSO-PS [39], an adapted GA with adjusting population size [40], adaptive biogeography based PPO [41], adaptive clonal selection algorithm [42], PSO [43], PSO, EP, GA, GWO and DE [44, 45] backtracking search optimization algorithm (BSOA) [46], opposition based GSA [47], a semi-definite programming-based model [48], a probabilistic multi-objective algorithm [49], improved ABC (IABC) [50–53], parallel NSGA-II [54]; a new Sine-Cosine algorithm (SCA) [55], safety barrier interior point [56], an improved gravitational search algorithm (EGSA) [57], improved group search optimization (IGSO) [58, 59], chaotic invasive weed optimization (CIWO) algorithms [7], a modified bacteria foraging algorithm (MBFA) [60], chance-constrained framework [61], the social spider optimization (SSO) algorithm [62], a modified Jaya algorithm [63], an improved DE algorithm integrated with effective constraint handling techniques [64], biogeography-based optimization (BBO) [65, 66], an enhanced strength Pareto evolutionary method [67], BAT [68], MOPF solution methodology [69, 70], an improved multi-objective multi-verse optimization (IMOMVO) algorithm [71], a quasi-oppositional cuckoo search (QOCS) [72], chaotic KHA [73], non-dominated sorting hybrid CSA [74], a hybrid algorithm of MSA with GSA [75], interior search algorithm (ISA) [76], forced initialized DE [70], a quasi-oppositional improved Jaya algorithm [77], glowworm swarm optimization (GSO) [78], multi objective ant lion algorithm (MALA) [79], improved colliding bodies optimization (ICBO) [80], a new mixed-integer nonlinear programming model [81], an improved firefly algorithm [82], a new TLBO using Lévy mutation strategy [83], a hybrid PSO with MVO [84], improved bat algorithm [85], DSA [86], hybrid PSOGSA [87], stud KHA [88], fuzzy harmony search (FHS) [89], adaptive FFA [90], modified MOEA/D [67, 91], electromagnetism-like algorithm (ELA) [92], enhanced self-adaptive DE [93] and moth swarm algorithm (MSA) [94].

The OPF problem can be mathematically expressed as:

$$Min\, F_{\mathrm{OPF}}(x, u) \tag{8}$$

$$Subject\ \ to:\ g(x, u) = 0 \tag{9}$$

$$h(x, u) \leq 0 \tag{10}$$

where F_{OPF} is the objective function, x is the state vector comprising P_{G1} (active power generation of slack bus generator), V_L (voltage magnitudes of load buses), Q_G (reactive power generations of generators) and S_l (apparent power flowing through transmission lines), respectively. Therefore, the x vector can be demonstrated as:

$$x^T = [P_{G1}, V_{L1} \ldots V_{LNPQ}, Q_{G1} \ldots Q_{GNG}, S_{l1} \ldots S_{lNTL}] \quad (11)$$

where NG is the number of generators; NPQ and NTL are the number of PQ buses and the number of transmission lines, respectively.u is the vector of decision variables comprising P_G (active power output of PV bus generators), V_G (generation bus voltages), T (transformer taps settings) and Q_C (shunt VAR compensation), respectively. Therefore, u can be stated as:

$$u^T = [P_{G2} \ldots P_{GNG}, V_{G1} \ldots V_{GNG}, Q_{C1} \ldots Q_{CNC}, T_1 \ldots T_{NT}] \quad (12)$$

where NT and NC show the numbers of tap-changing transformers and shunt compensation devices, respectively. From these variables, P_G and V_G are continuous variables and T and Q_C are discrete variables; and thus, the OPF problem is a mixed integer nonlinear optimization. For handling discrete variables, they are assumed as continuous variables with a suitable range and rounding is used in objective function to convert them to discrete variables. For example, if we want a discrete variable which can get any of the values {1, 2, 3, 4, 5}, we can define a continuous decision variable in the range [1,5.99] and use the floor function (integer part) for this variable at the start of objective function.

4.1.1. Constraints. *4.1.1.1. Equality constraints.* Typical load flow equations are expressed as (Pulluri et al. 2017):

$$P_{Gi} - P_{Di} - V_i \sum_{j=1}^{NB} V_j \left[G_{ij} \cos(\delta_i - \delta_j) + B_{ij} \sin(\delta_i - \delta_j) \right] = 0 \quad (13)$$

$$Q_{Gi} - Q_{Di} - V_i \sum_{j=1}^{NB} V_j \left[G_{ij} \sin(\delta_i - \delta_j) - B_{ij} \cos(\delta_i - \delta_j) \right] = 0 \quad (14)$$

where V_i and V_j are the voltages of ith and jth bus, respectively, NB is the number of buses, P_{Gi} and Q_{Gi} are the active and reactive power generations of generators, respectively, P_{Di} and Q_{Di} are the active and reactive load demands, respectively, G_{ij}, B_{ij} are the conductance and susceptance of the transmission line between bus i and bus j, respectively, and δ_{ij} is the phase difference of voltages between bus i and bus j.

4.1.1.2. Inequality constraints. In equality constraints include:

i. Generator related (Eqs. (15)–(17)), transformer tap settings (Eq. (18)), shunt VAR compensations (Eq. (19)) and security constraints (Eqs. (20) and (21)) [52]:

$$V_{Gi}^{\min} \le V_{Gi} \le V_{Gi}^{\max}, i = 1, \ldots, NG \quad (15)$$

$$P_{Gi}^{\min} \le P_{Gi} \le P_{Gi}^{\max}, i = 1, \ldots, NG \quad (16)$$

$$Q_{Gi}^{\min} \le Q_{Gi} \le Q_{Gi}^{\max}, i = 1, \ldots, NG \quad (17)$$

$$T_i^{\min} \le T_i \le T_i^{\max}, i = 1, \ldots, NT \quad (18)$$

$$Q_{Ci}^{\min} \le Q_{Ci} \le Q_{Ci}^{\max}, i = 1, \ldots, NC \quad (19)$$

$$V_{Li}^{\min} \le V_{Li} \le V_{Li}^{\max}, i = 1, \ldots, NPQ \quad (20)$$

$$S_{li} \le S_{li}^{\max}, i = 1, \ldots, NTL \quad (21)$$

where *min* and *max* indexes are the minimum and maximum limits of the variables, respectively.

4.1.2. Objective Functions. The objective functions are described as follow:

4.1.2.1. Minimization of the fuel cost. The fuel costs of the generators are usually modeled as quadratic functions. Consequently, the total fuel cost can be calculated as:

$$F_{\mathrm{OPF1}} = \sum_{i=1}^{NG} F_{Ci}(P_{Gi}) = \sum_{i=1}^{NG} \left(a_i + b_i P_{Gi} + c_i P_{Gi}^2 \right) \quad (22)$$

where F_{Ci} is the fuel cost of the ith generator and α_i, b_i and c_i are the cost coefficients of the ith generator.

4.1.2.2. Minimization of the real power losses (P_{Loss}). The total active power transmission loss is another objective function which is usually considered in solving the OPF problem and can be calculated as:

$$F_{\mathrm{OPF2}} = P_{Loss} = \sum_{\substack{k=1 \\ k=(i,j)}}^{NTL} G_k \left(V_i^2 + V_j^2 - 2 V_i V_j \cos \delta_{ij} \right) \quad (23)$$

4.1.2.3. Minimization of the voltage magnitude deviation (VD). Bus voltage magnitudes are important indices of system security. So, voltage profile enhancement should be considered as an objective function of OPF problem, as follows:

$$F_{\mathrm{OPF3}} = VD = \sum_{i=1}^{NPQ} | V_i - 1 | \quad (24)$$

where VD is the voltage deviation.

4.1.2.4. Emission objective. The pollutant emissions by generators are another objective function that is often considered in the OPF problem. Different types of gas emissions are produced by thermal generators, from which, two important types of emission gases, i.e. SO_X and NO_X, are considered here.

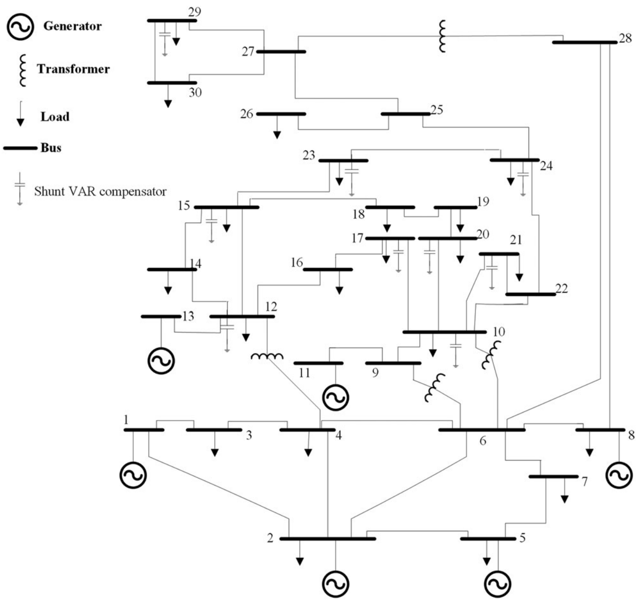

FIGURE 4. Single line diagram of IEEE 30-bus test system.

$$F_{\text{OPF4}} = \sum_{i=1}^{NG} F_{Ei}(P_{Gi}) = \sum_{i=1}^{NG} \left(\alpha_i + \beta_i P_{Gi} + \gamma_i P_{Gi}^2 + \xi_i \exp\left(\lambda_i P_{Gi}\right)\right) \tag{25}$$

where F_{Ei} denotes the emission of the ith generation unit. α_i, β_i, γ_i, ξ_i and λ_i represent the emission coefficients of ith unit, the first three related to SO_X and the last two related to NO_X.

It should be mentioned that the decision variables are self-constrained. The inequality constraints of $P_{G1,}$ V_L, Q_G, and S_l can be included in the objective function as quadratic penalty terms. Thus, the augmented objective function will be as:

where λ_P, λ_V, λ_Q and λ_S are penalty factors and n is the number of objective functions. x^{lim} is the limit value of the independent variable x and is given as:

$$x^{\text{lim}} = \begin{cases} x; \ x^{\min} \le x \le x^{\max} \\ x^{\max}; \ x > x^{\max} \\ x^{\min}; \ x < x^{\min} \end{cases} \tag{27}$$

The steps of implementing multi-objective TLSBO for solving optimal power flow problem are as follow:

Step 1: Input the required data for algorithm and power system.

Step 2: Convert the constrained optimization problem to an unconstrained one.

Step 3: Generate the algorithm's population of initial students.

Step 4: Calculate the objective functions for initial students.

Step 5: Store the dominant solutions in repository.

Step 6: Sort population of students taking into account the calculated normalized value of objective functions.

Step 7: Select teacher for initial students.

Step 8: Implement teaching phase using Eq. (1).

Step 9: Calculate the objective functions for new students.

Step 10: Store the dominant solutions in repository.

Step 11: Sort population of students taking into account the calculated normalized value of objective functions.

Step 12: Implement learning phase using Eq. (2).

Step 13: Calculate the objective functions for new students.

Step 14: Store the dominant solutions in repository.

Step 15: Sort population of students taking into account the calculated normalized value of objective functions.

$$J_{\text{OPF}}(x,u) = \begin{bmatrix} J_{\text{OPF1}}(x,u) \\ \cdot \\ \cdot \\ \cdot \\ J_{\text{OPF}n}(x,u) \end{bmatrix}_{n\times 1} = \begin{bmatrix} F_{\text{OPF1}} + \lambda_P\left(P_{G1} - P_{G1}^{\text{lim}}\right)^2 + \lambda_V \sum_{i=1}^{NPQ}\left(V_{Li} - V_{Li}^{\text{lim}}\right)^2 \\ +\lambda_Q \sum_{i=1}^{NG}\left(Q_{Gi} - Q_{Gi}^{\text{lim}}\right)^2 + \lambda_S \sum_{i=1}^{NTL}\left(S_{li} - S_{li}^{\text{lim}}\right)^2 \\ \cdot \\ \cdot \\ \cdot \\ F_{\text{OPF}n} + \lambda_P\left(P_{G1} - P_{G1}^{\text{lim}}\right)^2 + \lambda_V \sum_{i=1}^{NPQ}\left(V_{Li} - V_{Li}^{\text{lim}}\right)^2 \\ +\lambda_Q \sum_{i=1}^{NG}\left(Q_{Gi} - Q_{Gi}^{\text{lim}}\right)^2 + \lambda_S \sum_{i=1}^{NTL}\left(S_{li} - S_{li}^{\text{lim}}\right)^2 \end{bmatrix}_{n\times 1} \tag{26}$$

Variables	Limits Min	Max	Case 1	Case 2	Case 3	Case 4	Case 5	Case 6
P_{G1} (MW)	50	200	177.46	140.0	128.75	175.76	94.24	135.48
P_{G2} (MW)	20	80	48.6819	54.9997	50.8133	48.2834	60.8189	52.4040
P_{G5} (MW)	15	50	21.3137	24.1767	29.7327	21.3749	32.4291	26.6986
P_{G8} (MW)	10	35	20.8882	32.8789	35.0	20.7994	35.0000	34.9974
P_{G11} (MW)	10	30	11.8116	18.4732	24.9677	11.8583	30.0000	20.9056
P_{G13} (MW)	12	40	12.0	19.4771	19.7157	15.331	35.3941	19.2559
V_{G1} (p.u.)	0.95	1.1	1.1	1.0939	1.1	1.0419	1.0737	1.0832
V_{G2} (p.u.)	0.95	1.1	1.0817	1.0773	1.0865	1.022	1.0639	1.0678
V_{G5} (p.u.)	0.95	1.1	1.0508	1.0457	1.0594	1.0201	1.0385	1.0386
V_{G8} (p.u.)	0.95	1.1	1.0554	1.0562	1.0695	1.0094	1.0491	1.0470
V_{G11} (p.u.)	0.95	1.1	1.0838	1.0841	1.0746	0.9852	1.0785	1.0145
V_{G13} (p.u.)	0.95	1.1	1.0602	1.0575	1.0785	0.9976	1.0597	1.0331
$T_{6\text{–}9}$ (p.u.)	0.9	1.1	1.0397	1.0563	1.043	0.9983	1.0394	1.0754
$T_{6\text{–}10}$ (p.u.)	0.9	1.1	0.9667	0.9268	0.9549	0.9005	0.9408	0.9691
$T_{4\text{–}12}$ (p.u.)	0.9	1.1	0.9998	0.9847	1.0238	0.9635	0.9988	1.0551
$T_{28\text{–}27}$ (p.u.)	0.9	1.1	0.989	0.9948	0.9959	0.9631	0.9789	1.0057
Qc_{10} (p.u.)	0.0	0.05	0.05	0.02	0.03	0.05	0.04	0.05
Qc_{12} (p.u.)	0.0	0.05	0.03	0.03	0.01	0.03	0.04	0.0
Qc_{15} (p.u.)	0.0	0.05	0.05	0.05	0.05	0.05	0.04	0.02
Qc_{17} (p.u.)	0.0	0.05	0.05	0.0	0.04	0.0	0.05	0.05
Qc_{20} (p.u.)	0.0	0.05	0.04	0.05	0.05	0.05	0.04	0.05
Qc_{21} (p.u.)	0.0	0.05	0.05	0.04	0.05	0.05	0.05	0.05
Qc_{23} (p.u.)	0.0	0.05	0.03	0.03	0.02	0.05	0.04	0.05
Qc_{24} (p.u.)	0.0	0.05	0.05	0.05	0.05	0.05	0.05	0.05
Qc_{29} (p.u.)	0.0	0.05	0.03	0.04	0.03	0.02	0.03	0.02
Cost ($/h)			**799.4378**	**646.1931**	**822.0667**	**804.7501**	**865.0646**	**815.4377**
Losses (MW)			8.7559	6.6038	**5.5769**	10.0062	4.4789	**6.34**
VD (p.u.)			1.0847	1.04	1.2225	**0.0954**	1.0178	**0.3305**
Emission (ton/h)			0.3672	0.2829	0.2625	0.3614	**0.222**	**0.2742**

TABLE 3. Best (compromise) solutions for different cases of OPF using TLSBO algorithm.

Step 16: Repeat Steps 8 to 15 until the stopping criterion (here, maximum number of iterations) is satisfied.

4.1.3. Cases under Study. The algorithms have been used for solving single-objective and multi-objective OPF problems for different cases having different objective functions. To show the effectiveness of TLSBO algorithm, six different cases are considered as follows: cases 1 and 2 for single-objective OPF problems; and cases 3, 4, 5 and 6 for multi-objective OPF problems. The multi-objective optimization through Pareto dominance criteria is used for solving multi-objective OPF (MOOPF) problems as in [95].

Case 1: OPF: Minimization of fuel cost (Eq. (22))

Case 2: OPF: Minimization of piecewise quadratic fuel cost

In this case, in order to model the different fuels, the fuel cost function for the generators of buses 1 and 2 are considered to be piecewise quadratic functions.

$$F(P_{Gi}) = \begin{cases} \alpha_{i1} + b_{i1}P_{Gi} + c_{i1}P_{Gi}^2 & P_{Gi}^{\min} \le P_{Gi} \le P_{Gi1} \\ \alpha_{i2} + b_{i2}P_{Gi} + c_{i2}P_{Gi}^2 & P_{Gi1} \le P_{Gi} \le P_{Gi2} \\ \ldots & \\ \alpha_{ik} + b_{ik}P_{Gi} + c_{ik}P_{Gi}^2 & P_{Gik-1} \le P_{Gi} \le P_{Gi}^{\max} \end{cases} \tag{28}$$

where α_{ik}, b_{ik} and c_{ik} are cost coefficients of the ith generating unit for fuel type k. Augmented objective function can be defined as [96]:

$$J(x,u) = \left(\sum_{i=1}^{2} \alpha_{ik} + b_{ik}P_{Gi} + c_{ik}P_{Gi}^2\right) + \left(\sum_{i=3}^{NG} \alpha_i + b_iP_{Gi} + c_iP_{Gi}^2\right) + \lambda_P\left(P_{G1} - P_{G1}^{\lim}\right)^2 + \lambda_V \sum_{i=1}^{NPQ}\left(V_{Li} - V_{Li}^{\lim}\right)^2 + \lambda_Q \sum_{i=1}^{NG}\left(Q_{Gi} - Q_{Gi}^{\lim}\right)^2 + \lambda_S \sum_{i=1}^{NTL}\left(S_{li} - S_{li}^{\lim}\right)^2 \tag{29}$$

Algorithms	P_{G1} (MW)	P_{G2} (MW)	P_{G5} (MW)	P_{G8} (MW)	P_{G11} (MW)	P_{G13} (MW)	Cost ($/h)
CDE [97]	174.04	47.74	22.12	20.00	11.22	15.69	799.71
SKH [88]	177.14	48.64	21.31	21.26	11.97	12.0	800.51
PSOGSA [87]	177.22	48.75	21.39	21.10	11.97	12.00	800.49
GABC [52]	177.24	48.71	21.39	21.17	11.90	12.0	800.44
FHSA [89]	176.80	49.23	21.15	21.04	11.98	12.06	799.91
DSA [86]	176.95	48.71	21.38	21.29	12.04	12.0	800.39
TLBO	173.98	50.58	20.90	23.47	11.42	12.0	800.93
TLSBO	177.46	48.68	21.31	20.89	11.81	12.0	**799.44**

TABLE 4. Simulation results of different algorithms for Case 1 OPF.

Algorithms	P_{G1} (MW)	P_{G2} (MW)	P_{G5} (MW)	P_{G8} (MW)	P_{G11} (MW)	P_{G13} (MW)	Cost ($/h)
MDE [96]	140.0	55.0	24.0	34.989	18.044	18.462	647.846
MPSO-SFLA [95]	139.99	54.99	24.01	34.98	18.29	18.12	647.55
TLBO	140.0	54.9998	23.9516	33.9282	18.5698	18.9442	647.5579
TLSBO	140.0	54.9997	24.1767	32.8789	18.4732	19.4771	**646.1931**

TABLE 5. Simulation results of different algorithms for Case 2 OPF.

Algorithms	P_{G1} (MW)	P_{G2} (MW)	P_{G5} (MW)	P_{G8} (MW)	P_{G11} (MW)	P_{G13} (MW)	Losses (MW)	Cost ($/h)
EGA–DQLF [98]	–	49.5	30.06	34.98	23.96	21.374	5.613	822.87
FPSO [98]	–	59.88	34.62	33.4	30	23.56	5.6658	847.011
NSGA-II [99]	134.5544	46.2891	32.936	30.1163	18.735	26.5392	5.7699	823.8875
MOHS [99]	118.5673	51.5253	27.855	34.9822	28.6026	27.1048	**5.3143**	832.6709
TLBO	138.6	45.942	32.9026	27.1122	27.268	18.1248	6.5508	824.3649
TLSBO	128.75	50.8133	29.7327	35	24.9677	19.7157	5.5769	**822.0667**

TABLE 6. Simulation results of different algorithms for Case 3 OPF.

Case 3: OPF: MOOPF considering the fuel cost and P_{Loss}

$$J_{\mathrm{OPF}}(x,u) = \begin{bmatrix} J_{\mathrm{OPF1}}(x,u) \\ J_{\mathrm{OPF2}}(x,u) \end{bmatrix} \tag{30}$$

Case 4: OPF: MOOPF considering the fuel cost and *VD*

$$J_{\mathrm{OPF}}(x,u) = \begin{bmatrix} J_{\mathrm{OPF1}}(x,u) \\ J_{\mathrm{OPF3}}(x,u) \end{bmatrix} \tag{31}$$

Case 5 OPF: MOOPF considering the fuel cost and emission

$$J_{\mathrm{OPF}}(x,u) = \begin{bmatrix} J_{\mathrm{OPF1}}(x,u) \\ J_{\mathrm{OPF4}}(x,u) \end{bmatrix} \tag{32}$$

Case 6 OPF: MOOPF considering the cost, P_{Loss}, *VD* and emission

$$J_{\mathrm{OPF}}(x,u)^T = [J_{\mathrm{OPF1}}(x,u), J_{\mathrm{OPF2}}(x,u), J_{\mathrm{OPF3}}(x,u), J_{\mathrm{OPF4}}(x,u)] \tag{33}$$

4.1.4. Numerical Results of Solving OPF Problem. The performance of the proposed TLSBO algorithm in solving single-objective and multi-objective OPF problems is investigated on standard IEEE 30-bus test power system, which is shown in Figure 4. The total system demand is 2.834 p.u. at 100 MVA base. The limit values of all variables are given in [52].

The stopping criterion is selected as $Iter_{max} = 100$, and the population size is set to $N = 60$, for the OPF problems. Penalty factors in (23) are chosen, $\lambda_P = 100,000,000$, $\lambda_V = \lambda_Q = 50,000$ and $\lambda_S = 1000$.

TLSBO algorithm was implemented in MATLAB 7.6 and was run on a Pentium IV E5200 PC 2 GB RAM. Best control variables' settings for different cases of OPF using

Alg.	P_{G1} (MW)	P_{G2} (MW)	P_{G5} (MW)	P_{G8} (MW)	P_{G11} (MW)	P_{G13} (MW)	VD (p.u.)	Cost ($/h)
DE [100]	183.13	47.44	18.73	16.15	11.8855	16.505	0.1357	805.2619
TLBO	185.3	47.22	19.36	20.19	10.0008	12.0189	0.1009	804.9781
TLSBO	175.76	48.28	21.37	20.79	11.8583	15.331	**0.0954**	**804.7501**

TABLE 7. Simulation results of different algorithms for Case 4 OPF.

Algorithms	P_{G1} (MW)	P_{G2} (MW)	P_{G5} (MW)	P_{G8} (MW)	P_{G11} (MW)	P_{G13} (MW)	Emission (ton/h)	Cost ($/h)
ISPEA2II [67]	91.9631	65.2762	31.2750	34.8884	29.8586	34.9898	0.2235	867.9828
ISPEA2 [67]	93.5847	65.2596	30.2426	34.1723	29.2745	35.8744	0.2234	865.9499
MPSO-SFLA [95]	97.11	61.19	31.47	35.0	30.0	35.11	0.2246	868.372
TLBO	94.83	60.809	32.1411	34.8981	30.0	35.4566	0.2225	865.0944
TLSBO	94.24	60.8189	32.4291	35.0	30.0	35.3941	**0.222**	**865.0646**

TABLE 8. Simulation results of different algorithms for Case 5 OPF.

Algorithms	Minimization of fuel cost, losses, emission and voltage magnitude deviation			
	Cost ($/h)	Losses (MW)	VD (p.u.)	Emission (ton/h)
TLBO	816.4994	7.5229	0.4268	0.2764
TLSBO	**815.4377**	**6.34**	**0.3305**	**0.2742**

TABLE 9. Simulation results of different algorithms for Case 6 OPF.

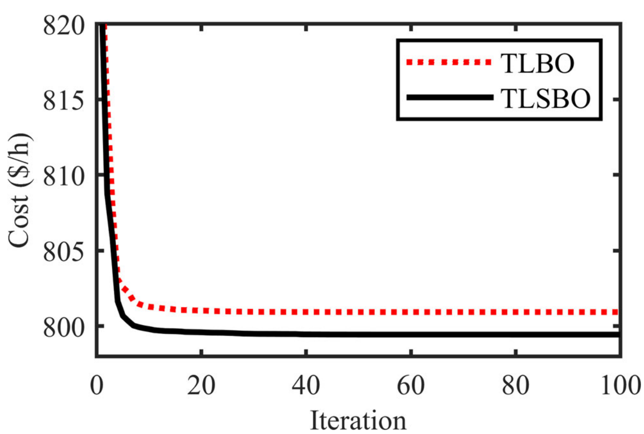

FIGURE 5. Convergence graph of TLBO and TLSBO algorithms for Case 1 OPF.

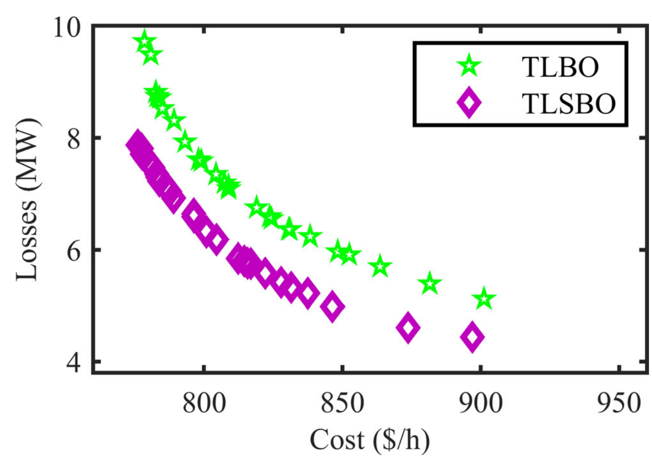

FIGURE 6. Pareto-optimal solutions achieved by TLBO and TLSBO algorithms for Case 3 OPF.

TLSBO algorithm are presented in Table 3. Furthermore, the best results and the best compromise solutions (BCS) calculated by TLSBO and other algorithms for different cases of the OPF problems are presented in Tables 4–9. In Tables 4–9 the best results are shown in bold fonts. It can be observed Judging in these tables that in cases 1, 2 and 4 to 6 the proposed TLSBO algorithm outperforms other optimization algorithms in recent literature and yields the minimum fuel cost ($/h), losses (MW), voltage magnitude deviation (VD (p.u.)) and emission (ton/h). In 3 of 4 MOOPF cases (case 4 to 6), the BCS of TLSBO Pareto-dominates the BCS of other algorithms. For case 3, the BCS of TLSBO Pareto-dominates the BCS of all other algorithms except for MOHS [99] which has lower losses than TLSBO.

Convergence graph of algorithms for case 1 is shown in Figure 5, and also, the Pareto optimal solutions achieved by TLBO and TLSBO algorithms for case 3 are illustrated in Figure 6. It is seen from Figure 5 that adding studying-phase to TLBO improves its convergence. Also, it is obvious from Figure 6 that TLSBO can achieve a very better Pareto front compared to TLBO, which proves the advantage of augmenting TLBO by studying-phase.

The above results obviously show that the proposed algorithm is a powerful algorithm for power system optimization. There are so many problems that can be solved by this algorithm, some of which can be found in [18, 101–106]. Furthermore, there are many enhancement methods that can be used for augmenting the performance of the proposed method.

5. CONCLUSION

TLBO is a population-based parameter-free simple optimization algorithm, which has shown better and acceptable performance on different engineering optimization problems. In this study a new version of TLBO algorithm, called TLSBO, is proposed by adding a new strategy, the studying strategy, to original TLBO. The proposed TLSBO algorithm was used for optimizing 12 benchmark real-parameter functions and various types of optimization problems and its results was compared with other optimal results reported in the previous literature. The simulation results demonstrate the proposed TLSBO algorithm has good, efficient and robust optimization performance with faster convergence characteristics for various types of optimization problems compared to the original TLBO and many previously presented algorithms as well.

Improving TLSBO by using the concepts like chaos, Levy Flight, multi-group, etc., and also hybridizing the proposed algorithm with other successful metaheuristic methods may be the subject of future studies.

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APPENDIX

The details of the typical uni-modal and multi-modal real-parameter functions (F) that are selected to evaluate the effectiveness of the proposed algorithms are summarized as [27]:

F_1: Shifted Sphere (uni-modal, separable and scalable test function): $F_1(x) = \sum_{j=1}^{D} z_j^2$, $z = x - o$, $x = [x_1, x_2, \ldots, x_D]$, $o = [o_1, o_2, \ldots, o_D]$: the shifted global optimum. with $x_j \epsilon [-100]$ and $F(x^*) = 0$.

F_2: Shifted Schwefel's Problem 1.2 (uni-modal, non-separable and scalable teat function):

$$F_2(x) = \sum_{j=1}^{D}\left(\sum_{jj=1}^{j} z_{jj}\right)^2, \; z = x - o, \; x = [x_1, x_2, \ldots, x_D],$$
$$o = [o_1, o_2, \ldots, o_D]\text{: the shifted global optimum.}$$

F_3: Shifted Rotated High Conditioned Elliptic (uni-modal, non-separable and scalable test function), $F_3(x) = \sum_{j=1}^{D} (10^6)^{\frac{j-1}{D-1}} z_j^2$, $z = (x - o) * M$, $x = [x_1, x_2, \ldots, x_D]$, $o = [o_1, o_2, \ldots, o_D]$: the shifted global optimum and, M: orthogonal matrix with $x_j \epsilon [-100]$ and $F(x^*) = 0$.

F_4: Shifted Schwefel's Problem 1.2 with Noise in Fitness (uni-modal, non-separable and scalable test function):-
$F_4(x) = \left(\sum_{j=1}^{D} \left(\sum_{t=1}^{j} z_t\right)^2\right) * (1 + 0.4|N(0, 1)|)$, $z = x - o$, $o = [o_1, o_2, \ldots, o_D]$: the shifted global optimum with $x_j \epsilon [-100]$ and $F(x^*) = 0$.

F_5: Schwefel's Problem 2.6 with Global Optimum on Bounds (uni-modal, non-separable and scalable test function):

$$F_5(x) = \max\left\{\left|A_j x - B_j\right|\right\},$$
$$A \text{ is a } D * D \text{ matrix, } A_j \text{ is the } j \text{ th row of } A, \; B_j = A_j * o.$$

with $x_j \epsilon [-100]$ and $F(x) = 0$.

F_6: Shifted Rosenbrock's (multi-modal, non-separable and scalable test function): $F_6(x) = \sum_{i=1}^{D-1} (100(z_j^2 - z_{j+1})^2 + (z_j - 1)^2)$, $z = x - o + 1$. with $x_j \epsilon [-100]$ and $F(x^*) = 0$.

F_7: Shifted Rotated Griewank's Function without Bounds (multi-modal, non-separable and scalable test function $F_7(x) = \sum_{j=1}^{D} \frac{z_j^2}{4000} - \prod_{j=1}^{D} \cos\left(\frac{z_j}{\sqrt{j}}\right) + 1$, $z = (x - o) * M$. with $x_j \epsilon [-600, 600]$ and $F(x^*) = 0$.

F_8: Shifted Rotated Ackley's with Global Optimum on Bounds (multi-modal, non-separable and scalable test function): $F_8(x) = -20\exp\left(-0.2\sqrt{\frac{1}{D}\sum_{j=1}^{D} z_j^2}\right) - \exp\left(\frac{1}{D}\sum_{j=1}^{D}\cos(2\pi z_j)\right) + 20 + e,\ z = x - o$ with $x_j \in [-32.0, 32.0]$ and $F(x^*) = 0$.

F_9: Shifted Rastrigin's (multi-modal, separable and scalable test function), $F_9(x) = \sum_{j=1}^{D}(z_j^2 - 10\cos(2\pi z_j) + 10),\ z = x - o$. with $x_j \in [-5.0, 5.0]$ and $F(x^*) = 0$.

F_{10}: Shifted Rotated Rastrigin's Function (multi-modal, non-separable and scalable test function), $F_{10}(x) = \sum_{j=1}^{D}(z_j^2 - 10\cos(2\pi z_j) + 10),\ z = (x - o) * M$. with $x_j \in [-5.0, 5.0]$ and $F(x^*) = 0$.

F_{11}: Shifted Rotated Weierstrass Function (multi-modal, non-separable and scalable test function), $F_{11} = \sum_{i=1}^{D}\left(\sum_{k=0}^{k\max}\left[a^k\cos(2\pi b^k(z_i + 0.5))\right]\right) - D\sum_{k=0}^{k\max}\left[a^k\cos(2\pi b^k)\right]$, $a = 0.5b = 3k\max = 20$ with $x_j \in [-5.0, 5.0]$ and $F(x^*) = 0$.

F_{12}: Schwefel's Problem 2.1 Function (multi-modal, non-separable and scalable test function), $F_{12} = \sum_{i=1}^{D}(A_i - B_i(x))^2,\ A_i = \sum_{j=1}^{D}(a_{ij}\sin\alpha_j + b_{ij}\cos\alpha_j),\ B_i(x) = \sum_{j=1}^{D}(a_{ij}\sin x_j + b_{ij}\cos x_j)$, with $x_j \in [-\pi, \pi]$ and $F(x^*) = 0$. a_{ij}, b_{ij} are integer random numbers in the range $[-100]$, α are random numbers in the range $[-\pi, \pi]$.

BIOGRAPHIES

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