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An application of teaching–learning-based optimization for solving the optimal power flow problem with stochastic wind and solar power generators

Mohd Herwan Sulaiman [a,*], Zuriani Mustaffa [b], Muhammad Ikram Mohd Rashid [a]

[a] *Faculty of Electrical & Electronics Engineering Technology, Universiti Malaysia Pahang, 26600 Pekan Pahang, Malaysia*
[b] *Faculty of Computing, Universiti Malaysia Pahang, 26600 Pekan Pahang, Malaysia*

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ABSTRACT

This paper proposes the implementation of metaheuristic algorithm namely, teaching–learning-based optimization (TLBO) algorithm to solve optimal power flow (OPF) problem. TLBO is inspired by philosophy of teaching and learning in the classroom. OPF on the other hand, is one of the most complex problems in power system operation, where in this paper, two objective functions aimed to be minimized by TLBO namely cost minimization and combined cost and emission (CEE) minimization. The effectiveness of proposed TLBO in solving the OPF is tested on modified IEEE-57 bus system that integrated with stochastic wind and solar power generations. To show the effectiveness of the proposed TLBO, several recent algorithms that have been proposed in literature will be utilized and compared. The simulations demonstrate the superiority of TLBO as an effective alternative solution for the OPF problems, where for the cost minimization, TLBO able to obtained 0.16% cost saving per hour compared to the second best algorithm; and for the CEE minimization, TLBO outperformed the second best algorithm by 0.12% cost saving per hour.

1. Introduction

Optimization problems can be seen in various fields from engineering design, business planning, internet routing until holiday planning, which represent from simple tasks to complex problems. The aims for optimization can be anything, to minimize the energy consumption and costs, to maximize the profit, output, performance, and efficiency [1]. The importance of optimization theory has led to the presence of many optimization methods, specifically based on nature inspired or sometimes is referred as metaheuristic algorithms.

Basically, the nature inspired algorithms can be classified into four clusters namely evolutionary-based, swarm-based, physics-based, and human-based algorithms. In evolutionary based, the introduction of Genetic Algorithm (GA) [2,3] and its variants have been proposed in literature in various applications such as in complex nonlinear system in glycerol metabolism [4], mechanical characterization of biosamples using a MEMS microgripper [5], calculation of soil electrical conductivity [6] and many more. Other algorithms that fall into evolutionary based are Genetic Programming (GP) [7] and Differential Evolution (DE) [8]. The application of GP into selection of functional parameter of the ψ-Caputo fractional derivative has been proposed in [9] and energy management system that emphasize on residential energy flows has been discussed in [10], while for DE, there are numerous optimization applications have been solved by DE and its variants such as in population interaction networks [11], unmanned aerial vehicle multitasking [12], and many others.

* Corresponding author.
E-mail address: herwan@ump.edu.my (M.H. Sulaiman).

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Nomenclature

Abbreviations

ACO	Ant Colony Optimization
AGV	Airport Automated Guided Vehicles
ANN	Artificial Neural Network
BB–BC	Big Bang–Big Crunch
CDE	Chaotic local search-based Differential Evolution
CEE	Cost and Emission
CMA-ES	Covariance Matrix Adaptation Evolution Strategy
DE	Differential Evolution
DTBO	Driving Training-Based Optimization
FACTS	Flexible AC transmission System
GA	Genetic Algorithm
GP	Genetic Programming
GSA	Gravitational Search Algorithm
HEBO	Heteroscedastic Evolutionary Bayesian Optimization
MFO	Moth Flame Optimization
NFL	[No Free Lunch]
OPF	Optimal Power Flow
PDF	Probability Density Function
PSO	Particle Swarm Optimization
PV	Photovoltaic
SHADE	Success History Based Adaptive DE
SPMGTLO	Single Phase Multi-Group Teaching–Learning Algorithm
TLBO	Teaching–Learning-Based Optimization
UPFC	Unified Power Flow Controller
WEDM	Wire-Electrical-Discharge-Machining
WOA	Whale Optimization Algorithm

Symbols

P_{TG}	total power output from thermal generators
c_{tax}	carbon tax
P_{Gi}	real power generation at bus i
Q_{Gi}	reactive power generation at bus i
P_{Di}	real power demand at bus i
Q_{Di}	reactive power demand at bus i
V_{Gi}	voltage magnitude at generation bus i
V_{Lm}	voltage magnitude at load bus m
Q_{Ck}	injected MVAR (capacitance) at bus k
T_n	transformers tap setting at line n
S_{lq}	line capacity at line p-q

Swarm-based optimization algorithms is started from the introduction of Particle Swarm Optimization (PSO) in 1995 by Eberhart and Kennedy [13], followed by various algorithms such as Ant Colony Optimization (ACO) [14], Moth Flame Optimization (MFO) [15], Artificial Bee Colony (ABC) [16], Whale Optimization Algorithm (WOA) [17] and others which can be obtained in literature. These outstanding swarm-based algorithms have been used as an optimizer tool for solving various fields of optimization problems such as PSO for gravity dam analysis [18], ACO for Airport Automated Guided Vehicles (AGV) path optimization [19], MFO for optimal operation of multiple effect evaporator of paper mills [20], ABC for optimizing the fractional order PID controller for DC brushless motor [21] and WOA for a two-degree-of-freedom fractional order proportional–integral–derivative (2FOPID) controller in automatic drug delivery control scheme during chemotherapy [22].

The third cluster of nature inspired optimization is called physic-based, where the algorithm is motivated from the universe phenomena such as Gravitational Search Algorithm (GSA) [23], Big Bang–Big Crunch optimization (BB–BC) [24], and Space Gravitational Algorithm (SGA) [25]. Finally, the fourth cluster is known as human-based optimization algorithms that mimic the human behavior and interaction such as Teaching–Learning Based Optimization (TLBO) [26,27], which is based on teaching and learning process in classroom and Driving Training-Based Optimization (DTBO) [28], which is the recent optimizer that categorized in this cluster based on the human activity of driving training.

In order to enhance the performance of the algorithms in solving real optimization problems, numerous hybrid algorithms have been proposed such as hybrid Artificial Neural Network (ANN) with DE in solving Traffic Sign Images [29], hybrid PSO-GA for pyrolysis kinetics of biomass determination [30], hybrid GA–GSA algorithm for tuning damping controller parameters for a unified power flow controller (UPFC) [31] and hybrid TLBO and Tabu Search for integrated selection and scheduling of projects [32]. It is also worth to mention that several improved versions of the mentioned algorithms have been proposed in literature by using the Bayesian inference, chaotic based and covariance matrix adaptation. These improvements normally used to improve the weakness of the premature convergence of original version of nature inspired algorithms such as Heteroscedastic Evolutionary Bayesian Optimization (HEBO) [33], Chaotic local search-based Differential Evolution (CDE) [34] and Covariance Matrix Adaptation Evolution Strategy (CMA-ES) [35] where the later algorithm is implemented for reducing the number of generations required for convergence to the optimum and belong to evolutionary-based cluster.

From the extensive literature reviews, it can be observed that the usage of nature inspired algorithms into solving real application of optimization problems are increasing from year to year. Thus, in this paper, the application of TLBO into solving complex optimization problem in power system is proposed. Power system is one of the complex networks in the world that consists of generation, transmission, distribution, and auxiliary components to supply the electricity to the various loads. It is expected that the power system to operate at optimal condition so that the maximum security and reliability can be achieved. One of the research topics that received attention from researchers all over the world is to solve the Optimal power flow (OPF) problem. This is due to the OPF solution involving the non-convex, large scale and non-linear constrained optimization problems. It is aimed to find the optimal control variables of power systems' components such as real power generations, generator's voltages, transformers setting, reactive compensation elements etc. hence, the minimization of objective functions can be obtained. During the optimization process, the power flow balanced, generators and transmission capabilities as well as voltage profile constraints must be satisfied [36].

To date, there are various metaheuristic algorithms that have been proposed in literature to solve OPF. The application of differential evolution (DE) into OPF solution has been presented in [37] followed by its variants namely success-history based DE (SHADE) [38] and improved adaptive DE [39], which considering the effect of the renewable energy into cost of generation in OPF solution. The employment of differential-based harmony search algorithm has been proposed in [40] for determining the optimal control variables of OPF solution. Ref. [41] proposes the improvement of Jaya algorithm to be applied in OPF problem namely adaptive multiple teams perturbation-guiding Jaya (AMTPG-Jaya).

Even though numerous algorithms have been proposed to solve the OPF problems, most of the solutions are trying to solve the OPF without the presence of renewable energy sources. It is worth to highlight that the similar work has been proposed in [42] where the TLBO has been applied in solving for IEEE 30 and IEE 118-bus systems and the implementation of TLBO for OPF of HVDC also has been proposed in [43]. Due to the no free lunch (NFL) theorem, the implementation of TLBO into different setting and type of the problems provide a significant difference as well as performances. The contributions of this paper can be listed as follow:

- The implementation of TLBO into OPF solution on the well-known IEEE 57-bus system with considering the integration of stochastic wind and solar power generators, which is different with the case studies and scenarios that have presented in [42].
- Conducting comparative studies among TLBO and existing metaheuristic algorithms reported in the OPF solution field.
- Two cases of single objective of OPF solution by TLBO: cost minimization and cost with emission effect minimization.

The rest of the paper is organized as follows: Section 2 discusses the OPF formulation followed by the brief description of TLBO in Section 3. The implementation of TLBO in solving OPF is presented in Section 4 and followed by the simulation studies in Section 5. Finally, Section 6 states the conclusion of this paper.

2. Optimal power flow problem formulation

The main purpose of OPF is to find the optimal setting of control variables in power system components to minimize the selected objective functions while satisfying all the equality and inequality constraints. In this paper, two objectives are identified to solve OPF for the system that consists of thermal and stochastic wind-solar power generations: (1) cost of generation minimization and (2) cost with emission effect minimization.

Cost of generation minimization

The first objective function is the cost of generation minimization, F_1, which represented as follows:

$$F_1 = \min(Cost) \tag{1}$$

where *Cost* is the total cost for generating power from thermal and renewable sources. For thermal generating units, the total cost that include the valve loading effects, $C_T\left(P_{TG}\right)$ is expressed as follows:

$$C_T\left(P_{TG}\right) = \sum_{i=1}^{N_{TG}} a_i + b_i P_{TGi} + c_i P_{TGi}^2 + \left| d_i \cdot \sin\left[e_i \cdot \left(P_{TGi}^{min} - P_{TGi}\right)\right]\right| \tag{2}$$

where P_{TG} is the total power output from thermal generators, a_i, b_i, c_i, d_i and e_i denote the cost coefficients of respected generator P_{TGi} with valve loading effect consideration, P_{Tgi}^{min} is the minimum setting of power of ith generator and N_{TG} is the number of thermal generators in the system.

Table 1
Coefficients for thermal generators for modified IEEE 57-bus system.

Generator	Bus	a	b	c	d	e	α	β	γ	ω	μ
P_{TG1}	1	0	2.00	0.00375	18	0.037	4.091	−5.554	6.49	2E−04	2.860
P_{TG2}	2	0	1.75	0.0175	16	0.038	2.543	−6.047	5.638	5E−04	3.333
P_{TG3}	3	0	3.00	0.0250	13	0.041	6.131	−5.555	5.151	1E−05	6.670
P_{TG4}	6	0	2.00	0.00375	18	0.037	3.491	−5.754	6.390	3E−04	2.660
P_{TG5}	8	0	1.00	0.0650	14	0.040	4.258	−5.094	4.586	1E−06	8.000

For the renewable sources, the cost of wind and solar generators are divided into several conditions namely direct cost, reserve cost and penalty cost, where the detail to obtain these costs can be obtained in [38].

Generation and emission cost minimization

The second objective function is to consider the minimization of generation and emission costs by imposing the carbon tax to reduce the greenhouse gases emission which can be defined as follows:

$$F_2 = F_1 + c_{tax} \cdot E \tag{3}$$

where c_{tax} represents the carbon tax, which is set to 20 ($/h) and E is the emission in tonnes per hour (t/h) which is calculated as follows [38]:

$$E = \sum_{i=1}^{N_{TG}} \left[\alpha_i + \beta_i P_{TGi} + \gamma_i P_{TGi}^2\right] \times 0.01 + \omega_i e^{(\mu_i P_{TGi})} \tag{4}$$

where α_i, β_i, γ_i, ω_i *and* μ_i are all emission coefficients corresponding to the ith thermal generator which is shown in Table 1.

Constraints

In solving the OPF problem, all the feasible solutions need to fulfill all the equality and inequality constraints. For equality constraint, the power balance equation for real and reactive power must be satisfied and expressed as follow:

$$P_{Gi} - P_{Di} - V_i \sum_{j=1}^{nB} V_j \left[G_{ij} cos\left(\delta_{ij}\right) + B_{ij} sin\left(\delta_{ij}\right)\right] = 0 \ \forall i \in nB \tag{5}$$

$$Q_{Gi} - Q_{Di} - V_i \sum_{j=1}^{nB} V_j \left[G_{ij} sin\left(\delta_{ij}\right) - B_{ij} cos\left(\delta_{ij}\right)\right] = 0 \ \forall i \in nB \tag{6}$$

where δ_{ij} is the difference of voltage angles between bus i and bus j, P_{Gi} and Q_{Gi} are the real and reactive power generation at bus (including wind and solar power), P_{Di} and Q_{Di} are the real and reactive load at bus i and nB is the total number of buses in the system.

The inequality constraint on the other hand, are the operating limits of the power system components which can represented as follow:

$$P_{TGi}^{min} \le P_{TGi} \le P_{TGi}^{max} I = 1, \ldots, N_{TG} \tag{7}$$

$$Q_{TGi}^{min} \le Q_{TGi} \le Q_{TGi}^{max} I = 1, \ldots, N_{TG} \tag{8}$$

$$V_{Gi}^{min} \le V_{Gi} \le V_{Gi}^{max} I = 1, \ldots, N_G \tag{9}$$

$$V_{Lm}^{min} \le V_{Lm} \le V_{Lm}^{max} m = 1, \ldots, N_L \tag{10}$$

$$Q_{ck}^{min} \le Q_{ck} \le Q_{ck}^{max} k = 1, \ldots, N_{Qc} \tag{11}$$

$$T_n^{min} \le T_n \le T_n^{max} n = 1, \ldots, N_T \tag{12}$$

$$S_{lq} \le S_{lq}^{max} q = 1, \ldots, N_{line} \tag{13}$$

where Eqs. (7) and (8) represent the real and reactive power generation limits for thermal power, respectively. Constraints on voltage of generator buses is shown in (9), while Eq. (10) is the constraints inflicted for load buses. The limitation of injected MVAR and transformer tap setting are expressed in (11) and (12), respectively, while Eq. (13) is the line capacity constraints. N_G, N_L, N_{Qc}, N_T and N_{line} are the total number of generator, total number of load, total number of injected reactive elements, total number of transformer and total number of transmission line in the system, respectively. It is worth to highlight that the inequality constraints for renewable energy sources can be obtained in [38] and all these constraints are satisfied by using the power flow program (MATPOWER) [44] to ensure the accurate results can be obtained.

3. Teaching–Learning Based Optimization (TLBO)

A TLBO is inspired by the teaching and learning process in the classroom invented by [26,27] which later arouse numerous debate regarding the discrepancies such as the terms, flowchart, pseudo code and the program code as mentioned in [45,46]. Nevertheless, as far as NFL theorem is concerned, the different types of setting and problems also can give different results and interpretations. Thus, this work is using the program that has been developed by [47] which has catered all the issues raised by [45].

Similar with other metaheuristic algorithms, TLBO uses population-based solution where the population is treated as a group or a class of learners, the design variables are analogues to subjects offered to learners and the learners' result is analogues to the 'fitness'. The process of acquiring knowledge is divided into teacher and learner phases and the teacher is considered as the best solution so far [42]. Pseudo code of TLBO algorithm can be obtained in [45].

TLBO has been proposed in 2011, and up until now the applications of TLBO into various optimization problems are keep increasing. This can be seen with encouraging works such as in reliability assessment of a floating offshore wind turbine mooring system [48], performance characteristics of aero-engine in Wire-electrical-discharge-machining (WEDM) [49] and energy consumption optimization of WEDM [50], abrupt motion tracking [51], optimum design of reinforced concrete counterfort retaining walls with minimum cost [52] and many more. TLBO becomes one of the choices as optimizer since there is no parameter needs to be tuned apart of population number and maximum iterations. This becomes the main advantage of TLBO compared to other metaheuristic algorithms in solving the optimization problems. Nevertheless, it depends on the problems to be solved since it may not perform well in other optimization problems subject to NFL theorem. It is also worth to highlight that the extension works of OPF with the presence of Flexible AC transmission System (FACTS) using TLBO with other six metaheuristic algorithms has been presented in [53], where TLBO is outperformed to all selected algorithms.

4. TLBO for OPF solution

In general, OPF solution can be defined as follows:

$$\begin{aligned} &\text{Minimize } F(x,u) \\ &s.t \qquad g(x,u)=0 \\ &\qquad\quad\ h(x,u)\le 0 \end{aligned} \tag{14}$$

where $F(\boldsymbol{x},\ \boldsymbol{u})$ is the objective function, $g(\boldsymbol{x},\ \boldsymbol{u})$ is the equality constraints and $h(\boldsymbol{x},\ \boldsymbol{u})$ is the inequality constraints. $\boldsymbol{X}$ and $\boldsymbol{u}$ are the control and state variables respectively since in power system, to obtain the optimality, not only the control variable; the state variables also play a vital role for the security of the power system operation. The set of control and state variables in OPF solution can be expressed as follow:

$$u^T = \left[P_{G2}\cdots P_{G_{NG}}, V_{G1}\cdots V_{G_{NG}}, T_1\cdots T_{N_T}, Q_1\cdots Q_{c_k}\right] \tag{15}$$

$$x^T = \left[P_{G_1}, Q_{G_1}\cdots Q_{G_{NG}}, V_{L_1}\cdots V_{L_m}\right] \tag{16}$$

where P_{G1} and Q_{G1} are the real and reactive power at the slack bus generation.

The application of the proposed TLBO in solving OPF problem is to find the optimal values of control variables to minimize all the objective functions that have been discussed in previous section while fulfilling all the constraints. Initially, number of search agents or population and the maximum iteration are set. Then, all the function details such as boundary of searching areas and the function evaluation (minimization of objective functions) are determined followed by plotting the lognormal PDF and Weibull fitting for solar PV and wind farm power evaluation, respectively. Each set of solution are mapped into the load flow data and load flow MATPOWER program is executed to obtain the selected objective (Cases 1 and 2). It is worth to highlight that the penalty function is enforced for the violation of inequality constraints of real power at slack bus, voltage magnitude at load buses, reactive power generations as well as line flow limits, which can be expressed as follows:

$$penalty = \lambda_P\left(P_{G1}-P_{G1}^{lim}\right)^2 + \lambda_V\sum_{i-1}^{NL}\left(V_{Li}-V_{Li}^{lim}\right)^2 + \lambda_Q\sum_{i-1}^{NG}\left(Q_{Gi}-Q_{Li}^{lim}\right)^2 + \lambda_S\sum_{q=1}^{Nl}\left(S_{lq}-S_{lq}^{lim}\right)^2 \tag{17}$$

where λ_P, λ_V, λ_Q and λ_S are the penalty factors. General flow of TLBO application into OPF problem is depicted in Fig. 1.

5. Results and discussion

Case 1: Generation cost minimization

Simulations for solving OPF are executed using MATLAB and the modified IEEE 57-bus system is used for all cases. IEEE 57-bus system can be considered as medium-scale problem that consists of 57 buses, 7 generators, 17 transformers and 42 loads. The modification is to include a single solar PV generator and wind farm at buses 9 and 12 respectively, as shown in Fig. 2. Tables 1 and 2 show the coefficients of thermal generators with valve-loading effects and PDF/ Weibull parameters with coefficients for stochastic model of solar PV plant and wind farm, respectively. The stochastic model is developed based on running of 8000 Monte-Carlo scenarios which can be obtained in detail in [38]. The population of TLBO is set to 30 and the maximum iteration is set to 500. For all simulations, 33 control variables need to be optimized that consist of real power generation, voltage at generator buses, transformers tap setting and reactive compensation elements while the number of state variables are 58 viz. real power generation at

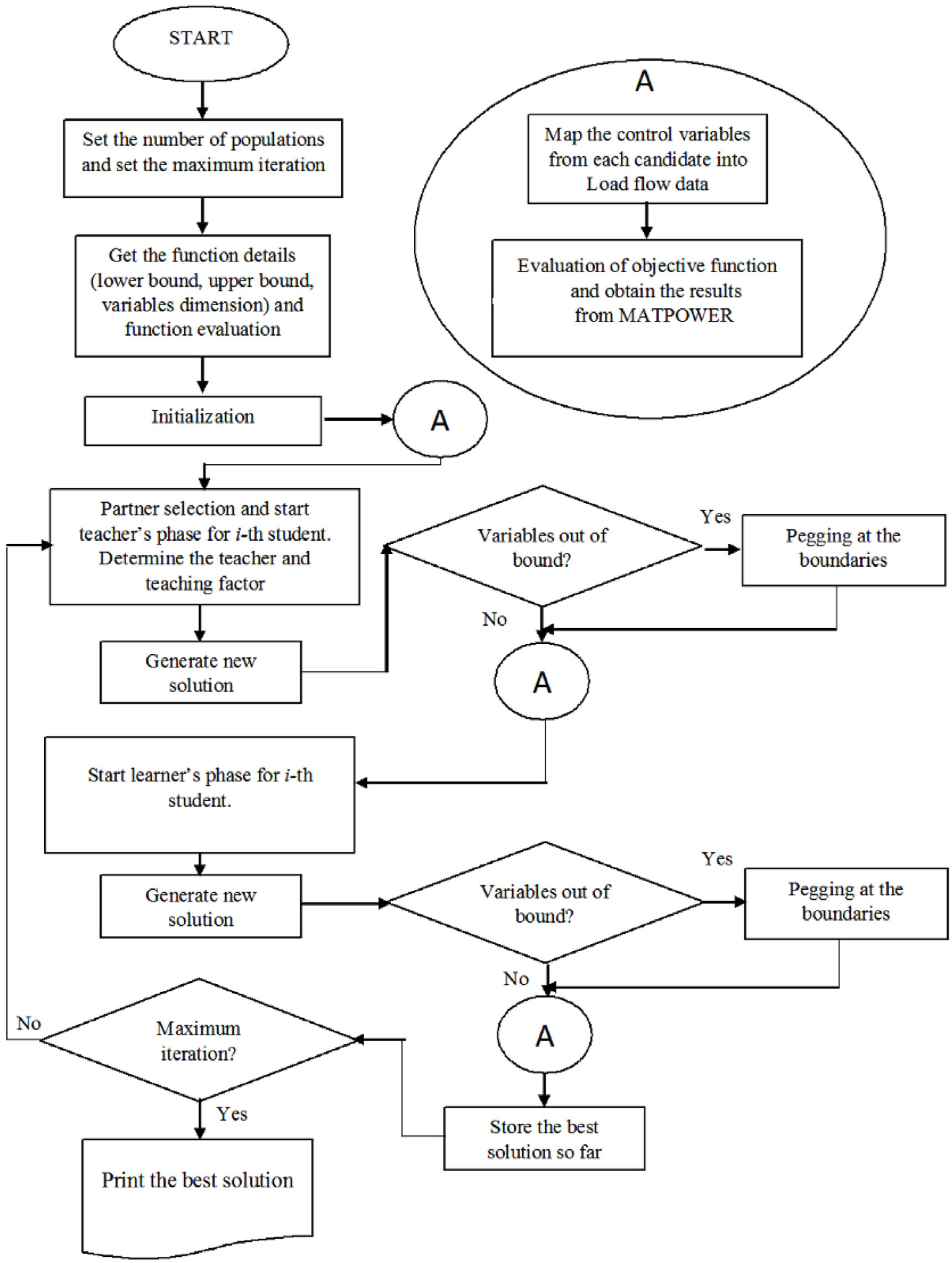

Fig. 1. Flow of TLBO for solving OPF problem.

slack bus, reactive power generation and voltage at load buses. In this case, the objective is to minimize the cost of power generation including the stochastic wind and solar PV power generators that have been presented in Section 2. All these setting have been used for all cases to obtain fair results for all simulations.

Table 2
PDF parameters and coefficients for solar PV plant at bus 9 and wind farm at bus 12.

Rated power	Lognormal/ Weibull PDF parameters	Direct cost coefficient ($/MW)	Reserve cost coefficient ($/MW)	Penalty cost coefficient ($/MW)
200 MW	$\mu = 6, \sigma = 0.6$	$g_{SG} = 1.6$	$K_{RS} = 3$	$K_{PS} = 1.5$
210 MW	$\alpha = 9, \beta = 2$	$g_{WG} = 1.6$	$K_{RW} = 3$	$K_{PW} = 1.5$

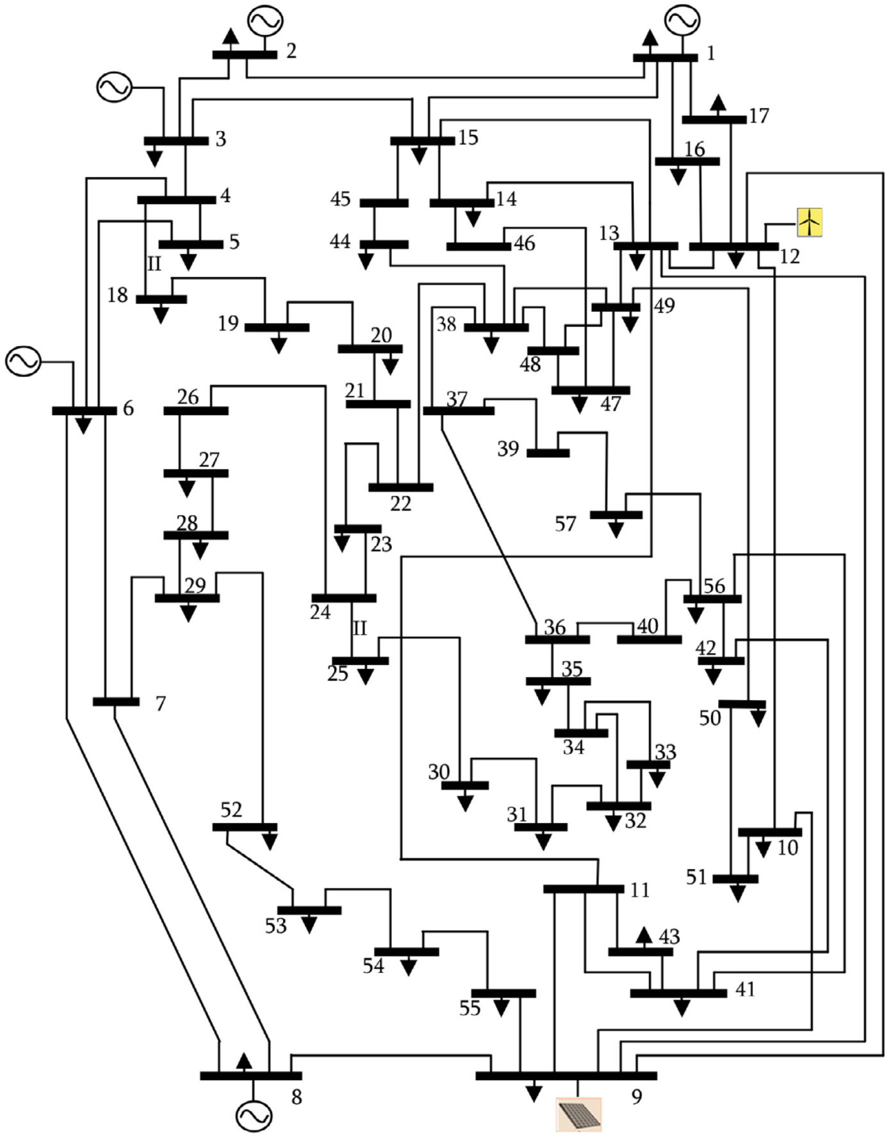

Fig. 2. Modified IEEE 57-bus system.

Table 3 shows the detail results of the control variables with slack generator at bus 1 obtained by TLBO together with the selected metaheuristic algorithms viz. variant of TLBO namely, Single Phase Multi-Group Teaching–Learning Algorithm (SPMGTLO) that has been proposed by [54,55], PSO, MFO and Jaya algorithm. These results are obtained from 10 free run of simulations. From this table, it can be seen that TLBO outperformed other compared algorithms which is highlighted in boldface. Cost of thermal, solar and wind power generators also included in this table. TLBO achieved the minimum cost of generation, 5099.5670 $/h and the second-best result is obtained by Jaya algorithm which produces 5107.9015 $/h. The difference results obtained between TLBO with the Jaya algorithm is 8.3345 $/h which is about $8.3345/h 0.16% cost saving per hour. The worst result is obtained by PSO where the significant cost saving from TLBO compared to PSO is 31.5149 $/h. This shows the effectiveness of TLBO compared to other algorithms.

Table 3
Detail results for different algorithms on Case 1.

Components	Min limit	Max limit	TLBO*	TLBO	SPMGTLO	PSO	MFO	JAYA
P_{G1}	0	575.88	575.8522	553.7501	555.8995	533.0303	558.1888	558.7459
P_{G2}	0	100	99.9948	100	99.9452	100	100	98.5073
P_{G3}	0	140	79.1035	76.6221	76.4172	98.1212	76.587	76.1663
P_{G6}	0	100	100	100	99.9955	100	100	100
P_{G8}	0	550	65.7673	50.3601	50.5518	57.8741	51.0499	48.8577
P_{G9}	0	200	164.3404	199.9998	199.9836	200	200	200
P_{G12}	0	210	209.9780	210	210	210	210	210
V_{G1}	0.95	1.1	1.0783	1.0946	1.1	1.1	1.0723	1.0917
V_{G2}	0.95	1.1	1.0993	1.0956	1.0854	1.1	1.0396	0.95
V_{G3}	0.95	1.1	1.0748	1.0564	0.95	0.95	1.1	1.0926
V_{G6}	0.95	1.1	1.1000	0.9618	0.9974	0.95	1.0521	1.0766
V_{G8}	0.95	1.1	1.0286	1.0299	0.981	1.1	1.0819	1.031
V_{G9}	0.95	1.1	1.0998	0.969	0.9797	1.1	1.1	1.0673
V_{G12}	0.95	1.1	1.0879	1.0199	0.9947	1.056	1.0571	1.0182
$T_{19(4-18)}$	0.9	1.1	0.9795	1.0113	0.9957	0.9	1.06	1.1
$T_{20(4-18)}$	0.9	1.1	1.0702	0.9535	0.9073	1.1	1.074	0.9502
$T_{31(21-20)}$	0.9	1.1	0.9380	0.9977	0.9967	0.9152	0.9613	1.0132
$T_{35(24-25)}$	0.9	1.1	0.9979	0.9018	0.9325	0.9	0.9911	0.9262
$T_{36(24-25)}$	0.9	1.1	0.9035	0.9463	0.9316	1.1	0.9169	1.0092
$T_{37(24-26)}$	0.9	1.1	1.0323	0.9717	0.9782	1.1	1.0636	0.9916
$T_{41(7-29)}$	0.9	1.1	0.9911	0.9569	0.9185	0.9125	0.9895	1.0053
$T_{46(34-32)}$	0.9	1.1	0.9068	0.9123	0.9	0.9	0.9611	0.9215
$T_{54(11-41)}$	0.9	1.1	0.9186	0.9	0.9	0.9	0.9002	0.9547
$T_{58(15-45)}$	0.9	1.1	0.9944	0.9825	0.9598	0.9	0.9	0.9807
$T_{59(14-46)}$	0.9	1.1	0.9688	0.9656	0.9435	1.1	1.0262	0.9776
$T_{65(10-51)}$	0.9	1.1	0.9309	0.9744	0.9417	1.0581	1.0108	0.9506
$T_{66(13-49)}$	0.9	1.1	0.9106	0.9354	0.9	1.1	0.9786	0.9169
$T_{71(11-43)}$	0.9	1.1	0.9712	0.9543	0.9165	0.9	1.0203	0.9552
$T_{73(40-56)}$	0.9	1.1	0.9462	0.9819	1.0417	1.1	1.1	1.0783
$T_{76(39-57)}$	0.9	1.1	1.0224	0.9483	0.9573	1.1	0.9549	0.9
$T_{80(9-55)}$	0.9	1.1	0.9692	0.9602	0.9261	1.1	1.1	0.979
Q_{C18}	0	5	4.4952	4.999	4.4454	5	1.6959	2.9977
Q_{C25}	0	5	3.7605	4.9998	4.9991	5	5	4.5789
Q_{C53}	0	5	0.1627	5	4.998	0	0.2571	4.6656
$F_{Cost}(PT_G)$			5618.0362	3480.3368	3493.1646	3575.1155	3511.9508	3488.7704
$F_{Cost}(PW)$			–	877.563	877.563	877.563	877.563	877.563
$F_{Cost}(PS)$			–	741.5671	741.4935	741.5681	741.5681	741.5681
F_{Cost} (\$/h)			5618.0362	**5099.467**	5112.2211	5194.2466	5131.0819	5107.9015

Table 4
Statistical results for different algorithms on Case 1.

Performance	TLBO	SPMTLO	PSO	MFO	JAYA
Best	**5099.47**	5112.22	5194.25	5131.08	5107.90
Worst	**5163.48**	5275.27	6870.77	5778.91	5706.38
Average	**5112.11**	5171.97	5651.54	5336.54	5337.05
Std Dev.	**19.84**	45.68	493.36	199.39	236.39

From this table, the results of TLBO without the presence of renewable energy sources also have been included, which is marked with TLBO*. It can be seen that the total cost obtained is the worst compared to the algorithms that consider the renewable energy sources. This is due to the burden of the power generation at bus 9 has been transferred to the slack generator which is boosting the total cost of the power generation. It also can be noted from the table that all algorithms gave the optimal results within the specified limits that have been set for the simulation. In order to show the effectiveness of TLBO compared to other identified algorithms, the statistical analysis in terms of the best, worst, average and standard deviation results are presented in Table 4. It can be noted that TLBO outperformed all algorithms for all performances. These results are further visualized in boxplot which is shown in Fig. 3. These results are based on the 10 running of simulations on the similar platform for fair comparison. The convergence curve for all algorithms in solving this case is depicted in Fig. 4. It can be concluded that all algorithms are converged within 400 iterations.

Case 2: Generation cost and emission minimization

In this case, the generation cost that including the emission effect is considered as the objective function to be minimized. Table 5 shows the best of detail results obtained for all algorithms in 10 runs of simulation. Again, it can be seen that TLBO outperformed other compared algorithms in terms of obtaining the minimum cost of generation productions with the effect of carbon tax which is highlighted in boldface. TLBO achieved the minimum cost of generation viz. 5 137.1759 \$/h followed by SPMGTLO that produces 5 143.7169 \$/h and the worst result is obtained by PSO which produces 5 327.4771 \$/h. It is about 0.12% cost saving per hour obtained by TLBO compared to SPMGTLO. This shows the significant cost saving obtained by the TLBO compared to other algorithms. Again, the results of TLBO without the presence of renewable energy sources also have been included, which is

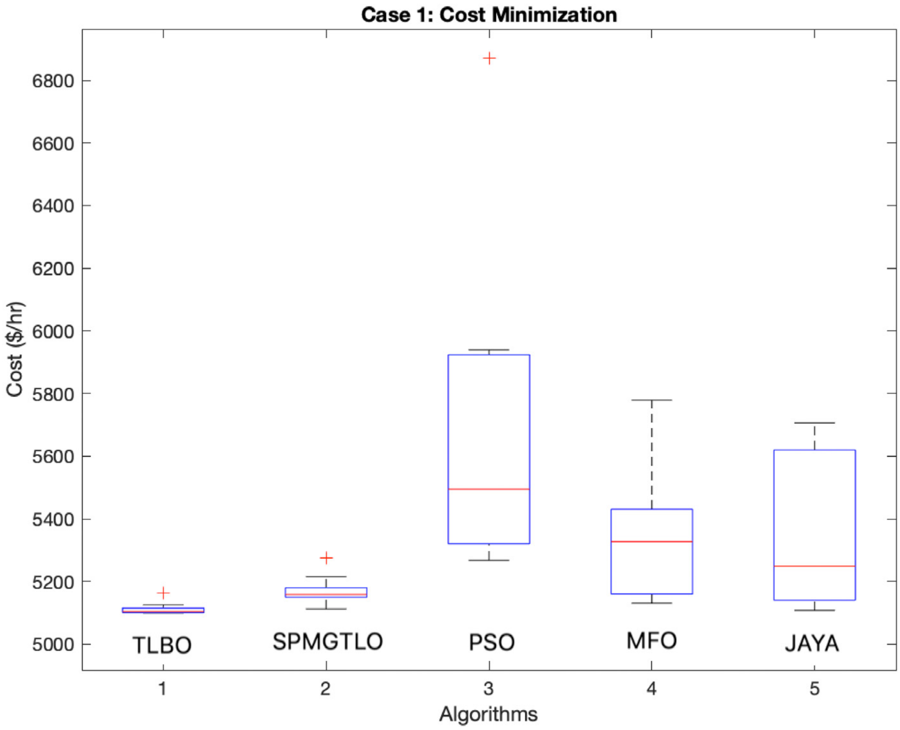

Fig. 3. Boxplot for Case 1.

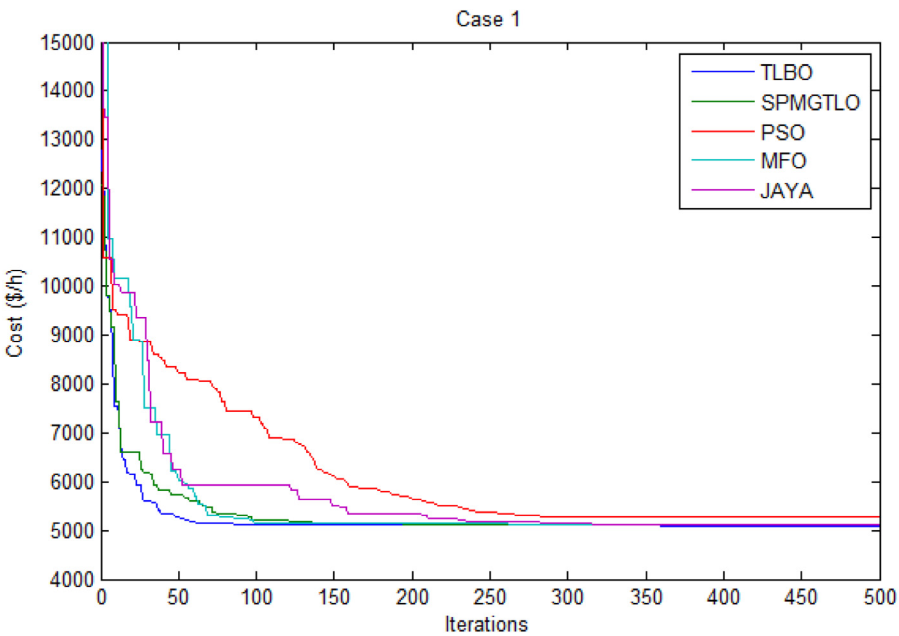

Fig. 4. Convergence curve for all algorithms of Case 1.

marked with TLBO*. It can be seen that the total cost and emission obtained is the worst compared to the algorithms that consider the renewable energy sources. Even though the power output from the slack generator is close to the results obtained by PSO, nonetheless the total cost is much higher from PSO, which is more than $ 300 per hour. This shows that the impact of renewable energy sources is significant in this case study.

Table 5
Detail results for different algorithms on Case 2.

Components	TLBO*	TLBO	SPMGTLO	PSO	MFO	JAYA
P_{G1}	575.8531	551.3482	552.7697	573.187	553.1109	556.3354
P_{G2}	*99.9948*	99.9998	99.9895	90.2279	100	100
P_{G3}	*79.1035*	76.6263	76.5963	83.5045	76.5811	78.1542
P_{G6}	*100*	100	99.9889	100	100	100
P_{G8}	*65.7673*	52.3202	51.9601	72.877	52.3119	50.6847
P_{G9}	*164.3404*	199.9995	199.9974	175.2296	200	199.9077
P_{G12}	*209.9780*	209.9993	209.998	210	209.9974	210
V_{G1}	*1.0783*	1.0894	1.0921	1.0496	1.1	1.1
V_{G2}	*1.0993*	1.0987	0.95	1.1	1.1	1.0835
V_{G3}	*1.0748*	1.0602	1.0514	1.1	1.0513	0.9562
V_{G6}	*1.1*	1.0842	0.95	0.95	1.0557	0.95
V_{G8}	*1.0286*	1.0285	1.0286	1.1	1.0584	0.9837
V_{G9}	*1.0998*	0.95	1.0921	1.1	1.0959	0.9707
V_{G12}	*1.0879*	1.0288	1.0243	1.1	1.0384	0.9651
$T_{19(4-18)}$	*0.9795*	1.0117	0.9935	1.1	1.0307	0.9237
$T_{20(4-18)}$	*1.0702*	0.9933	0.9623	0.9817	1.1	0.9
$T_{31(21-20)}$	*0.9380*	1.0387	0.9857	0.9598	0.9	1.0596
$T_{35(24-25)}$	*0.9979*	0.9518	0.951	1.0427	0.9819	0.9051
$T_{36(24-25)}$	*0.9035*	0.9047	0.9	0.9	0.9	0.9028
$T_{37(24-26)}$	*1.0323*	0.9796	0.9763	1.1	0.9961	0.9886
$T_{41(7-29)}$	*0.9911*	0.9633	0.9632	0.9	1.0006	0.9202
$T_{46(34-32)}$	*0.9068*	0.9148	0.9131	0.9456	0.9118	0.9348
$T_{54(11-41)}$	*0.9186*	0.9	0.9	1.1	0.9	0.9149
$T_{58(15-45)}$	*0.9944*	0.9873	0.982	1.0631	0.9	0.9283
$T_{59(14-46)}$	*0.9688*	0.9656	0.98	0.9	0.9661	0.9004
$T_{65(10-51)}$	*0.9309*	0.9716	0.9784	0.9962	0.9947	0.9213
$T_{66(13-49)}$	*0.9106*	0.9321	0.9	1.1	0.9726	0.9058
$T_{71(11-43)}$	*0.9712*	0.9573	0.9538	0.9	1.0244	0.9287
$T_{73(40-56)}$	*0.9462*	0.9867	1.0041	0.9	1.1	1.0611
$T_{76(39-57)}$	*1.0224*	0.9547	0.9519	1.1	0.9	0.9287
$T_{80(9-55)}$	*0.9692*	0.9623	0.9621	1.1	0.9842	0.9467
Q_{C18}	*4.4952*	4.3293	4.9499	5	1.5475	0.4121
Q_{C25}	*3.7605*	4.9998	4.9581	0	4.9986	3.3599
Q_{C53}	*0.1627*	5	4.9831	5	5	5
$F_{Cost}(PT_G)$	*5618.0362*	3479.6743	3485.5033	3779.6057	3490.141	3509.735
$F_{Cost}(PW)$	–	877.5599	877.5538	877.563	877.5511	877.563
$F_{Cost}(PS)$	–	742.9475	742.9378	630.3961	742.9496	742.5293
F_{Cost} (\$/h)	5618.0362	5100.1817	5105.9949	5287.5648	5110.6417	5129.8273
F_{CE} (\$/h)	5662.4504	**5137.1759**	5143.1769	5327.4771	5147.8689	5167.492

Table 6
Statistical results for different algorithms on Case 2.

Performance	TLBO	SPMTLO	PSO	MFO	JAYA
Best	**5137.18**	5143.18	5327.48	5148.20	5167.49
Worst	**5303.42**	5516.42	6227.51	5462.69	5348.69
Average	**5172.72**	5254.48	5692.03	5287.62	5253.90
Std Dev.	**57.66**	119.44	249.48	102.20	77.85

The statistical results for this case for all algorithms are tabulated in Table 6. Again, the performances of TLBO are the best compared to others. The boxplot for this case is exhibited in Fig. 5. From this figure, it can be seen that TLBO exhibits superior accuracy performance compared to other algorithms. The worst performance is obtained by PSO while MFO and JAYA gave quite close results. The second best performance is obtained by the SPMGTLO except for the worst results that are greater compared to MFO and JAYA. The convergence curve for all algorithms in solving this case is depicted in Fig. 6.

The performance of TLBO in solving both cases are further evaluated by performing the non-parametric Wilcoxon statistical test. The null hypothesis is accepted when the *p*-value is larger than the significance level (0.05), and vice versa. The performance is evaluated between TLBO with all compared algorithms, where a pairwise comparison is done between TLBO/SPMGTLO, TLBO/PSO, TLBO/MFO and TLBO/JAYA for both cases. The results of *p*-values are reported as metrics of significance as tabulated in Table 7. Based on this table, it can be observed that the proposed TLBO is significant over compared algorithms at *p*-value less than 0.05. In this case, the null hypothesis was rejected because TLBO is statistically significant for both cases of study.

6. Conclusion

In this paper, a metaheuristic algorithm namely TLBO has been proposed to solve OPF problem. To assess the performance TLBO in solving OPF problem, it has been applied into two different OPF objective functions: minimizations of generation cost

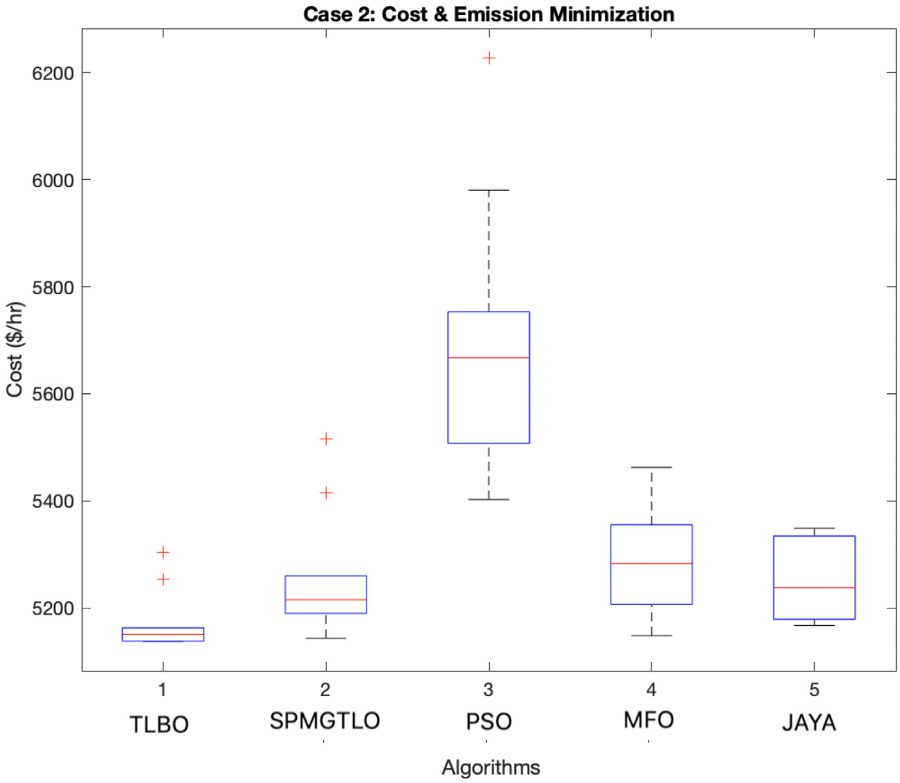

Fig. 5. Boxplot for Case 2.

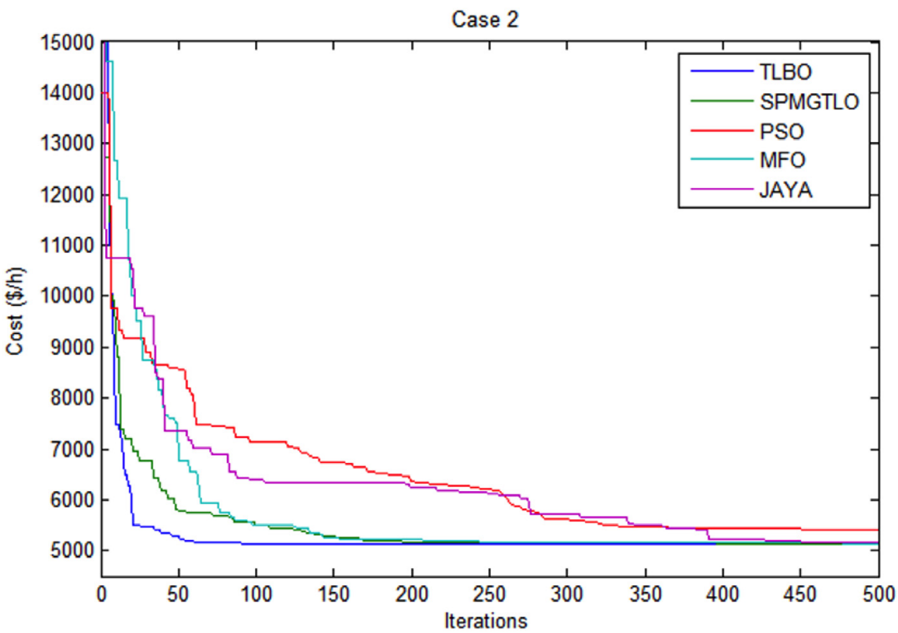

Fig. 6. Convergence curve for all algorithms of Case 2.

and generation cost that include emission effect on modified IEEE 57-bus system that consists of thermal, stochastic solar and wind power generators. Comparative analysis shows that TLBO produces very competitive performance and outperformed other selected algorithms for all cases. Even though the applications of TLBO into OPF problems have been done previously, the different

Table 7
P-values of the Wilcoxon rank sum test over cases.

Cases	SPMTLO	PSO	MFO	JAYA
Cost minimization (F1)	0.001706	0.000183	0.000440	0.000769
CE minimization (F2)	0.037635	0.000183	0.005795	0.004586

setting and testing problems may produce different significant performance and exhibit the superiority of TLBO. Therefore, it can be an effective alternative for solving the OPF problems. The implementation of TLBO into multi-objectives problems of OPF is still in progress and will be proposed in the near future. Even though the results obtained by TLBO outperformed all other selected algorithms, there is one issue or drawback of TLBO can be noticed. In TLBO, there is no parameter to be tuned apart of population number and maximum iteration. This can be treated as advantage as well as disadvantage which is depending on the problem to be solved. Since we deal with the NFL, where there is no optimization algorithm can solve all optimization problems. Thus, there is necessity to have at least one tuning parameter so that the TLBO can be performed well for solving more complex optimization problems, which also can be proposed in the future.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data can be obtained in MATPOWER toolbox.

Acknowledgments

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