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ORIGINAL PAPER

A new hybrid algorithm with genetic-teaching learning optimization (G-TLBO) technique for optimizing of power flow in wind-thermal power systems

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Abstract In this study, a new hybrid genetic teaching learning- based optimization algorithm is proposed for wind-thermal power systems. The proposed algorithm is applied to a 19 bus 7336 MW Turkish-wind-thermal power system under power flow and wind energy generation constraints and three different loading conditions. Also, a conventional genetic algorithm and teaching learning-based (TLBO) algorithms were used to analyse the same power system for the performance comparison. Two performance criteria which are fuel cost and algorithm run time were utilized for comparison. The proposed algorithm combines the specialties of conventional genetic and TLBO algorithms to reach the global and local minimum points effectively. The simulation results show that the proposed algorithm developed in this study performs better than the conventional optimization algorithms with respect to the fuel cost and algorithm run time for wind-thermal power systems.

Keywords A hybrid genetic-teaching learning-based optimization (G-TLBO) algorithm · Wind-thermal power systems · Fuel cost · Algorithm run time

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1 Introduction

The performance of a power flow system is related to some main conditions such as system constraints and the efficiency of executed optimal power flow (OPF) analysis algorithms. System constraints depend on the physical system devices which cannot be changed easily. The efficiency of power flow algorithms has progressed over the years. Power flow analysis is an important problem for the power systems to supply the electrical energy with good quality. The main goals of the OPF are to obtain the minimum fuel cost, minimum power loss and minimum algorithm run time. The most commonly considered objective function is total cost of generation [1]. Also, the OPF algorithm should be in accordance with some other important specialties such as less pollution for the environment and chemical reactions [2].

The variety in electrical power systems has increased over the years. Many new forms of electrical energy generation such as wind or solar energy have added to the conventional power systems in most countries of the world and global energy demand is set to grow by 37 % by 2040 in central scenario [3]. More advanced OPF algorithms to the different characteristics of these energy generation units should be to maintain the technical requirements and proper operation of an interconnected power system.

In the past years, a number of studies have been done about the first OPF algorithms such as Newton Raphson, Fast Decoupled Flow in different interconnected power systems [4,5]. Also, a great number of conventional algorithms have been suggested in the literature based on the conventional [6–12] and hybrid power flow techniques [13–19] but there is no research on solving the OPF problem by the proposed method on a hybrid energy generation system used in this study.

Genetic algorithm is an evolutionary and effective algorithm to reach the solutions of global minimum points. It is first invented by John Holland in the early 1970s [20]. However, GA has some convergence problems in optimization to arrive to the solutions of the local points.

TLBO is a new algorithm and was developed by Rao et al. [21]. It is a social-based algorithm which is based on interaction between a teacher and students in a class. Teacher is considered the most informed person and gives knowledge to his class.

Mostly, when evolutionary algorithms become weaker, working with other optimization methods can give better results. The power of evolutional algorithm is to determine the nearest points in the solution space. However, standard evolutional algorithms are weak in determining the fine tuning of candidate solutions. Hence, success of the algorithm will rise using a local optimization method on the results which are determined by evolutional algorithms. Based on the behaviours' overall performance in this environment, genetic and other operators are applied to improve the performance of the population of behaviours [22]. Hybrid algorithms are composed of two or more standard algorithms to combine the successful way of each algorithm.

The electrical energy system analysed in this paper is composed of 7336 MW thermal and wind energy production system in Turkey. These thermal sources are the biggest ones in the Country. According to wind energy installations and wind potentials in Turkey, 11 new wind bus [23] is added to the standard system and a thermal and wind power system are composed.

As new forms of renewable energy sources added to the conventional energy generation system, increasing algorithm run time becomes an important problem for the whole interconnected power system. Therefore, a new energy dispatching and optimization algorithm for conventional and renewable energy generation sources should be developed.

In this paper, a difference value (d_v) and a multiplier value (m_v) are chosen in GA part of the proposed algorithm and a student and a variable number are chosen in TLBO algorithm to improve the whole system performance. The comparison of the proposed algorithm, the standard TLBO algorithm and the standard genetic algorithm on the hybrid energy system, the proposed algorithm suggests that algorithm runtime with the proposed algorithm are better than the rest.

2 Optimal power flow (OPF)

In power system analysis and power control, OPF is used to obtain the optimum values of energy dispatching parameters such as algorithm run time, fuel cost, power loss, the best placement of capacitors. OPF is implemented an optimization algorithm under some determined constraints. These constraints are the limits of power devices used in power systems. The algorithms used in OPF should obtain the parameters as much as possible.

Algorithm run time is an elapsed time to arrive the best values of parameters. A better algorithm should reach the best solutions in a shorter time. Load dispatching centres decide the load increase or decrease by OPF software according to instantaneous system values such as frequency value and maintenance of generator units. Also, these centres decide which electric generation units will be in operation and how much of electrical load should be decreased or increased for electric quality. All of these decisions are made according to the values obtained from OPF algorithms. As new generation units have added to the conventional energy system, algorithm run time becomes much more important. The speed and quality of electric energy depends on the speed of the OPF algorithm. Because of these reasons, energy scheduling is inevitable [24].

OPF is composed of two main stages such as determining Hessian matrix and calculation of fuel cost. Hessian matrix is calculated to obtain the node-voltage equations for a power system, impedances are expressed in per unit on a common MVA base and for simplicity resistances are neglected [24]. Since the nodal solution is based upon Kirchoff's current law, impedances are converted to admittance as in Eq. 1,

$$y_{ij} = \frac{1}{z_{ij}} = \frac{1}{r_{ij} + jx_{ij}} \tag{1}$$

Each power generating unit has a typical operating cost curve which consists of a_i, b_i, c_i and d_i parameters. These parameters are related to heat rates of power generating units, which are determined by turbine or generator producers. Depending on the heat efficiency of fuel type, incremental heat rate in Btu/kWh -output power in MW curves for each thermal power generator are plotted. These curves can be formulated mathematically as quadratic equations defined by Eq. 14. a_i, b_i, c_i thermal power parameters are determined from these heat rate versus power curves. d_i is a parameter related to the wind generators. d coefficient is calculated from proportion of maximum generation of a wind turbine to rated power value according to power curve of a wind turbine curve which is provided by wind turbine producers.

Total system load is calculated as Eq. 2,

$$L = \left(\sum\nolimits_{i=1}^{ng} (P_{g_i}) + \sum\nolimits_{j=1}^{n_w} (w_j)\right) \tag{2}$$

Line losses for the real power transmission [25] are given by Eq. 3,

$$P_L = \sum\nolimits_{k=1}^{nl} g_k \left[V_i^2 + V_j^2 - 2V_i.V_j.\cos\left(\delta_i - \delta_j\right)\right] \tag{3}$$

where g_k is the conductance of a transmission line k connected between ith and jth bus, n_l is the total number of transmission lines, $V_i, V_j, \delta_i, \delta_j$ are the voltage magnitudes and phase angles of ith and jth bus, respectively.

OPF should be implemented under some constraints such as equality and inequality constraints. Also, extra constraints should be taken into consideration for the systems including other renewable electrical energy sources such as wind or solar. As equality constraints, generated and consumed power is defined in the Eqs. 4 and 5 [25],

$$P_{\text{load}} - \sum Pg_i - \sum P_L = 0 \quad (4)$$

$$Q_{\text{load}} - \sum Qg_i - \sum Q_L = 0 \quad (5)$$

where P_{load} and Q_{load} is the active and reactive power demanded by the system and $\sum Pg_i$ and $\sum Qg_i$ is the total active and reactive power generated by all generators and $\sum P_L$ and $\sum Q_L$ are total active and reactive line losses, respectively.

Inequality constraints can be classified into generator constraints, transformer constraints and security constraints. Generator constraints are minimum and maximum generator generation values. Here, the problem and also solution is to determine the optimum power generation values between minimum and maximum power limits and to determine the total load demand for the generators.

The optimum power for ith generator is given by Eq. 6,

$$P_{\min} \leq Pg_i \leq P_{\max} \quad (6)$$

where $P_{\min}$ is minimum value of ith generator, Pg_i is optimum generated power, $P_{\max}$ is maximum value of ith generator [25].

Generation constraints include generator voltages, generator active and reactive power generation limits.

Generator voltage limits are defined as Eq. 7,

$$V_{G_i}^{\min} \leq V_{G_i} \leq V_{G_i}^{\max}, \quad 1 \leq i \leq N_G \quad (7)$$

where $V_{G_i}^{\min}$ is the generator minimum limits and $V_{G_i}^{\max}$ is the generator maximum limits and N_G is the number of generators [25].

Generator active power limits are defined as Eq. 8,

$$P_{G_i}^{\min} \leq P_{G_i} \leq P_{G_i}^{\max}, \quad 1 \leq i \leq N_G \quad (8)$$

where $P_{G_i}^{\min}$ and $P_{G_i}^{\max}$ are minimum and maximum active power values of ith generator, respectively. N_G is the number of generators.

Generator reactive power limits are given by Eq. 9,

$$Q_{G_i}^{\min} \leq Q_{G_i} \leq Q_{G_i}^{\max}, \quad 1 \leq i \leq N_G \quad (9)$$

where $Q_{G_i}^{\min}$ and $Q_{G_i}^{\max}$ are minimum and maximum reactive power values of ith generator, respectively. N_G is the number of generators [26].

Interconnected power systems can include regulating transformers at some branches. This regulation is implemented by regulating transformer tap values which are taken as 1 normally. Tap value limits are stated as Eq. 10,

$$T_i^{\min} \leq T_i \leq T_i^{\max}, \quad 1 \leq i \leq N_T \quad (10)$$

where $T_i^{\min}$ and $T_i^{\max}$ are minimum and maximum tap values of ith transformer, respectively. N_T is the number of tap transformers [26].

Security constraints are voltage magnitudes at load bus and these are defined as Eq. 11,

$$V_{L_i}^{\min} \leq V_{L_i} \leq V_{L_i}^{\max}, \quad 1 \leq i \leq N_{PQ} \quad (11)$$

where $V_{L_i}^{\min}$ and $V_{L_i}^{\max}$ are minimum and maximum load voltages of ith bus, respectively. N_{PQ} is the number of active and reactive bus [26].

Wind power constraints are wind generator constraint and rated wind power from the ith wind-powered generator [27]. Wind generator constraints are powers at wind bus and these are defined as Eq. 12,

$$P_{i,\min} \leq P_i \leq P_{i,\max} \quad (12)$$

where $P_{i,\min}$ and $P_{i,\max}$ is minimum and maximum generated powers of ith wind turbine or ith wind field bus [27].

Rated wind power constraints are powers which are rated wind power from the ith wind-power generator and are stated as Eq. 13,

$$0 \leq w_i \leq w_{r,i} \quad (13)$$

where w_i scheduled wind power and $w_{r,i}$ rated wind power from the ith wind-powered generator [27].

V_j is an average wind speed which is determined annually by performing wind speed measurements at different locations. According to its value, real generated wind power is calculated using the power curve of a wind turbine. V_j average wind speed values are taken from General Directorate of Electric Power Resources Survey and Development Administration [28].

The fuel cost for conventional power systems can be expressed as the sum of each generator cost in Eq. 14,

$$F_{\text{costconv}} = \sum_{i=1}^{n_g} (\alpha_i + \beta_i Pg_i + \gamma_i Pg_i^2)\$/h \quad (14)$$

where α_i, β_i and γ_i are the fuel cost coefficients and Pg_i is the active power for the ith generator and n_g is the number of generators in the system.

If energy generation system has wind bus, total F_{cost} is stated as Eq. 15 [29],

$$\sum F_{\text{cost}} = F_{\text{costconv}} + \left(\sum_{i=1}^{n_w} C_{w_i}(w_i) + \sum_{i=1}^{n_w} C_{p,w_i}\left(W_{i,av} - w_i\right) + \sum_{i=1}^{n_w} C_{r,w,i}\left(w_{i-} W_{i,av}\right)\right) \$/h \quad (15)$$

where n_g is the number of conventional generators, n_w is the number of wind generators, Pg_i is the active power for the ith generator, $W_{i,av}$ is available wind power from the ith wind-powered generator, C_{w_i} is cost function for the ith wind-power generator, C_{p,w_i} is penalty cost function for not using all available power from the ith wind-powered generator, $C_{r,w,i}$ is required reserve cost function, relating to uncertainty of wind power.

If the wind generators are not owned by the system operator, C_{p,w_i} and $C_{r,w,i}$can be neglected and F_{cost} becomes as Eq. 16 [29],

$$F_{\text{cost}} = \left(\sum_{i=1}^{ng}\left(\alpha_i + \beta_i Pg_i + \gamma_i Pg_i^2 + \sum_j^{n_w}(d_j w_j)\right)\right) \$/h \quad (16)$$

where d_j is direct cost coefficient for the ith wind generator and w_j is scheduled wind power from jth wind-powered generator and n_w is the number of wind generators in the system. For simplicity, we neglected the penalty and required cost functions.

3 Thermal-wind-powered Turkish energy generation system of 19 Bus

For a local analysis, the proposed algorithm has been tested on a part of Turkish electrical network. In addition to 8 conventional thermal sources, 11 new wind-powered power generation units are added and totally 19 bus energy generation system has been arranged. Wind generators are supposed as not owned by the system operator so C_{p,w_i} and $C_{r,w,i}$ in Eq. 15 are neglected. All of those 19 energy generation plants are located in Aegean and Marmara regions which have the biggest thermal and wind-powered energy generation units. The system has electric power generation capacity of 1503 MW at minimum and 7689.05 MW at maximum. Bus numbers, power plant names, fuel types of power plants, α, β, γ, d fuel cost coefficients, V_i average wind speeds, minimum and maximum power generation limits and scheduled power values for each power plant are given in Table 1.

Some wind fields such as Kuyucak and Soma are composed of different capacity and different number of wind turbines. For example, Sayalar power plant (bus 16) is composed of 0.9 and 2 MW wind turbines. In this study, all of these units are taken as a separate generation bus. So, total number of bus is 23 separately.

Selected power plants have used up natural gas, fuel oil, coal and wind as energy source.

Each power plant has fuel cost coefficients. Thermal power plants have three fuel cost coefficients as α, β, γ. Wind-powered plants have only d fuel cost coefficient and α, β, γ coefficients are taken as 0 value [28]. d coefficient is calculated from proportion of maximum generation of a wind turbine to rated power value according to power curve of a wind turbine curve which is provided by wind turbine producers. d is generally taken as 1 value [28]. α, β, γ coefficients are states heat rates of thermal power plants and are calculated from power curve of the power plant [30].

$P_{i_{\min}}$, $P_{i_{\max}}$ and $P_{\text{imax}}^{\text{sch}}$ are the bus power values. Switching off a thermal power plant has very high cost; therefore, thermal power plants have to be operated at a minimum power value constantly. $P_{i_{\min}}$ for wind generation is taken as 0 value. $P_{i_{\max}}$is a turbine maximum value. P_{imax}^{sch} is a power value which is expected power generation. In this study, it is accepted as maximum power generation for thermal plants. For wind-powered electrical generation, $P_{\text{imax}}^{\text{sch}}$ has been calculated according to average wind speed and the power curves of wind turbines [31,32].

4 Used methods

In this study, Genetic Teaching Learning-Based Optimization (G-TLBO) Algorithm is proposed for conventional and wind-thermal power systems. The proposed algorithm is combined of conventional TLBO Algorithm and conventional GA. TLBO algorithm and GA are used for comparison to the proposed algorithm in terms of algorithm run time and fuel cost.

The effectiveness of three algorithms is compared on a part of Turkish electrical system which consists of totally 19 thermal and wind-powered bus. In some active or reactive power calculations, line losses can be neglected to see the efficiency of studied algorithm [33,34]. This study also neglects the reactive line losses.

4.1 TLBO algorithm

TLBO algorithm is a social-based optimization algorithm which depends on interaction between students and teachers in a class. The learning capacity of students is related to ability of teacher. Teacher tries to increase the level of students. At every step of algorithm, successful students are elected and the best students have been determined.

TLBO algorithm has three parameters which is the number of students, number of classes and iteration number. TLBO algorithm has two phase, these are teacher and learner phases.

Table 1 Location and power generation data for 19 bus power system [30–32]

Gen no.	Power plant	Fuel type	α_i (\$)	β_i (\$/MW)	γ_i (\$/MW^2)	d	V_i (m/s)	$P_{i_{\min}}$ (MW)	$P_{i_{\max}}$ (MW)	$P_{i_{\max}}^{\text{sch}}$ (MW)
1	Hamitabat	N. Gas	6595.5	7.0663	0.0168	0	0	190	1120	1120
2	Ambarlı	Fuel oil	7290.6	7.2592	0.1270	0	0	245	1350	1350
3	Dgaz	N. Gas	6780.5	5.6820	0.0106	0	0	318	1432	1432
4	Seyitömer	Coal	1564.4	3.1288	0.0139	0	0	150	600	600
5	SomaB	Coal	5134.1	6.2232	0.0168	0	0	210	990	990
6	Yeniköy	Coal	1159.5	3.3128	0.0210	0	0	110	420	420
7	Kemerköy	Coal	1697.0	3.2324	0.0137	0	0	140	630	630
8	Yatağan	Coal	1822.8	3.4720	0.0147	0	0	140	630	630
9	Akres	Wind	0	0	0	1	8	0	45	14.4
10	Çanta	Wind	0	0	0	1	6	0	35	6.27
11	Çatalca a	Wind	0	0	0	1	7	0	60	10.4
12	Dares Datça	Wind 28*0.8 MW	0	0	0	1.012	7	0	22.4	5.04
		8 * 0.9 MW	0	0	0	1.011	7	0	7.2	1.248
						Total		0	29.6	6.288
13	Karakurt	Wind	0	0	0	1	8	0	10.8	6
14	K. Burgaz	Wind	0	0	0	1.025	7	0	24	6.384
15	Kuyucak	Wind 2 MW	0	0	0	1.025	8	0	24	9.78
		0.9 MW	0	0	0	1.012	8	0	1.8	0.476
						Total		0	25.8	10.256
16	Sayalar	Wind 0.9 MW	0	0	0	1.011	8	0	34.2	9.044
		2 MW	0	0	0	1.025	8	0	20	8.150
						Total		0	54.2	17.194
17	Soma	Wind 0.9 MW	0	0	0	1.011	8	0	80.1	21.182
		2 MW	0	0	0	1	8	0	160	65.2
						Total		0	240.1	86.382
18	Sunjüt	Wind	0	0	0	1	7	0	1.2	0.2716
19	Tepe	Wind	0	0	0	1	7	0	0.85	0.225
Total power in MW								1503	7689	7336

At teacher phase of the algorithm, students learn from the teacher by imitating. A teacher gives the information between students and tries to increase the average of his class. Teacher is the most experienced and the most informed person so the best student can learn as much as the teacher.

Between teacher and student's learning capacity, there is an average difference called difference mean and it is defined as Eq. 17,

$$\text{Difference\_Mean}_{j,i} = r_i\left(X_{j,\text{kbest},i} - T_f M_{j,i}\right) \tag{17}$$

where r_i is a random number between 0 and 1, $X_{j,\text{kbest},i}$ is the result of teacher (the best result) and T_f is teaching factor between 1 and 2.
T_f is defined as Eq. 18,

$$T_f = \text{round}\left[1 + \text{rand}\left(0, 1\right)\{1, 2\}\right] \tag{18}$$

If difference mean is better than present result, Eq. 17 is arranged as Eq. 19,

$$X'_{j,k,i} = X_{j,k,i} + \text{Difference\_Mean}_{j,k,i} \tag{19}$$

where $X'_{j,k,i}$ is the best function result accepted.

After teacher's phase, all best function values are kept to use at student's phase.

At student phase, students learn the knowledge by interacting and by discussing between them. If a student is more knowledgeable, the other is updating himself by interaction.

P and Q are the random students, $X'_{\text{total}-P,i}$ and $X'_{\text{total}-Q,i}$ are given as Eq. 20,

$$X'_{\text{total}-P,i} \neq X'_{\text{total}-Q,i} \tag{20}$$

where $X'_{\text{total}-P,i}$ and $X'_{\text{total}-Q,i}$ are updated values of $X_{\text{total}-P,i}$ and $X_{\text{total}-Q,i}$

If $X'_{\text{total}-P,i} > X'_{\text{total}-Q,i}$, $X''_{j,P,i}$ is obtained as Eq. 21,

$$X''_{j,P,i} = X'_{j,P,i} + r_i(X'_{j,P,i} - X'_{j,Q,i}) \tag{21}$$

and if $X'_{\text{total}-Q,i} > X'_{\text{total}-P,i}$, $X''_{j,P,i}$ is calculated as Eq. 22,

$$X''_{j,P,i} = X'_{j,P,i} + r_i(X'_{j,Q,i} - X'_{j,P,i}) \tag{22}$$

$X''_{j,P,i}$ is accepted as the best function value [35].

4.2 Genetic algorithm (GA)

The idea in GA is to evolve a population of candidate solutions to a given problem, using operators inspired by natural genetic variation and natural selection [36].

Given a clearly defined problem to be solved and a bit string representation for candidate solutions, a simple GA works as follows:

1. Start with a randomly generated population of n (l-bit) chromosomes (candidate solutions to a problem).
2. Calculate the fitness $f(x)$ of each chromosome x in the population.
3. Repeat the following steps until n offspring have been created:

a. Select a pair of parent chromosomes from the current population, the probability of selection being an increasing function of fitness. Selection is done "with replacement," meaning that the same chromosome can be selected more than once to become a parent.
b. With probability pc (the "crossover probability" or "crossover rate"), cross over the pair at a randomly chosen point (chosen with uniform probability) to form two offspring. If no crossover takes place, form two offspring that are exact copies of their respective parents.
c. Mutate the two offspring at each locus with probability pm (the mutation probability or mutation rate), and place the resulting chromosomes in the new population. If n is odd, one new population member can be discarded at random.

4. Replace the current population with the new population.
5. Go to step 2 [36].

4.3 Proposed (G-TLBO) algorithm

The proposed algorithm has a hybrid structure which is composed of conventional genetic and TLBO algorithms. Two distinguished specialties of our proposed algorithm are fast selecting of the best students by GA determining a specific difference value (d_v) to reach the optimum power value or the best fuel cost. Standard TLBO algorithm needs the best students at the beginning of the algorithm at each iteration. GA selects the best students for TLBO algorithm using chromosome coding, roulette, crossover, penalty and tournament stages and d_v value determined by user. GA works quicker than TLBO algorithm in selection of the best students because of its efficiency at reaching the global minimum points. The main reason to use the GA in the proposed algorithm is to determine the intermediate power values as much as possible for the TLBO algorithm so total algorithm run time decreases substantially.

The proposed algorithm uses difference value (d_v) to obtain the best power generation value between minimum and maximum power constraints. Difference value (d_v) is an absolute value of difference between total power and demanded load and it is calculated in Eq. 23,

$$d_v = \text{abs}\left(\text{Total power} - \text{load}\right) \tag{23}$$

GA detects d_v value and executes it for each attempt to obtain the best fuel cost result. GA adds and subtracts the difference value (d_v) from minimum and maximum power values for each bus. GA arrives to a best optimum power value quickly rather than TLBO algorithm. That obtained G_{best} value using GA is students of TLBO algorithm.

Determining the difference value (d_v) is as equation 24 and 25,

$$\text{If } d_v \text{ is high from } P_{\max} - P_{\min}, \quad d_v = P_{\max} - P_{\min} \tag{24}$$

$$\text{If } d_v \text{ is below minimum } P_{\max}, \quad d_v = m_v * P_{\min} \tag{25}$$

where m_v is multiplier value and from experiences it can be between 1 and 50.

d_v difference value is selected according to findings of GA automatically so the best F_{cost} values are obtained at every attempt.

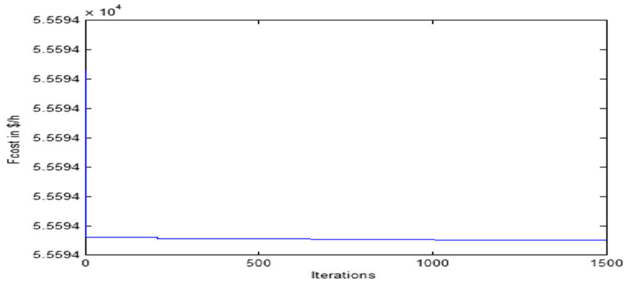

Fig. 1 Fuel costs by conventional GA under 25 % loading-1834 MW power demand

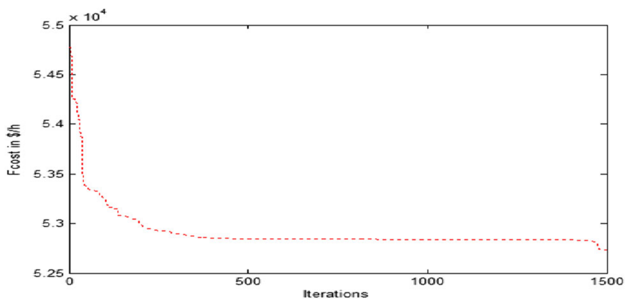

Fig. 2 Fuel costs by conventional TLBO algorithm under 25 % loading-1834 MW power demand

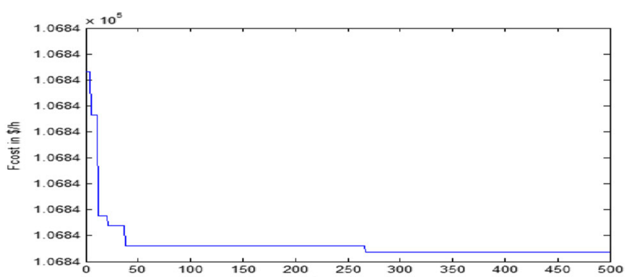

Fig. 3 Genetic section of the proposed algorithm under 25 % loading-1834 MW power demand

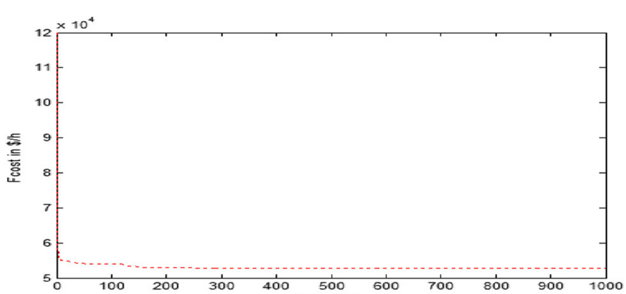

Fig. 4 TLBO algorithm section of the proposed algorithm under 25 % loading-1834 MW power demand

5 Simulation results

Simulations were performed using the conventional genetic and TLBO algorithms and the proposed algorithm in terms of algorithm run time and fuel cost. The algorithms were applied to a 19 bus thermal-wind-powered combined hybrid energy generation system. The same power system parameters were used in all algorithms for a comparison.

TLBO algorithm is applied with 10 students, 23 variables (23 separate bus) and 1500 iterations. In genetic section, crossover probability factor $p_c = 0.9$, mutation probability factor $p_m = 0, 2$, resolution= 2 and $m_v = 44$. The proposed algorithm has 1500 iterations. Conventional GA has 500 and

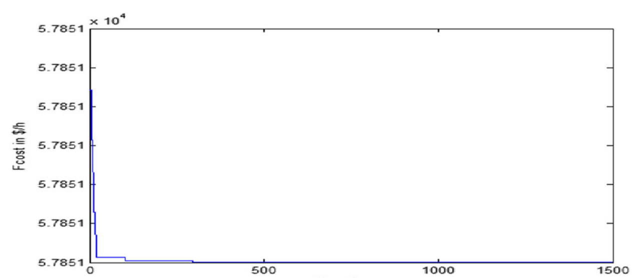

Fig. 5 Fuel costs by GA for hybrid 19 bus system under 27.5 % loading-2017 MW power demand

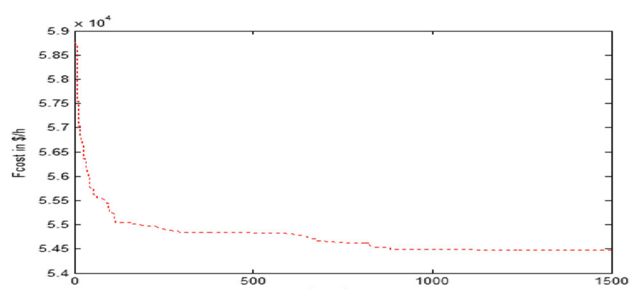

Fig. 6 Fuel costs by TLBO algorithm under 27.5 % loading-2017 MW power demand

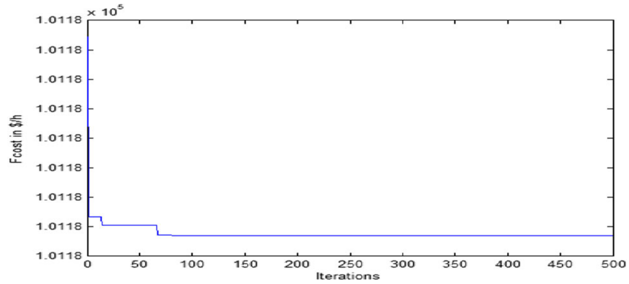

Fig. 7 Genetic section of the proposed algorithm under 27.5 % loading-2017 MW power demand

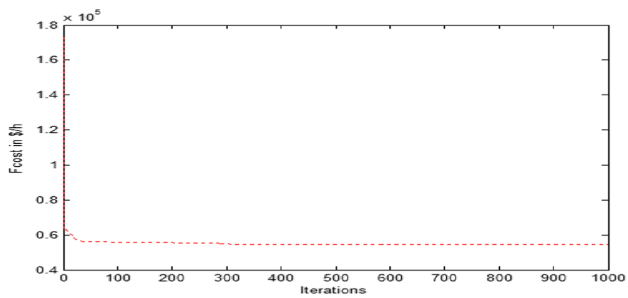

Fig. 8 TLBO algorithm section of the proposed algorithm under 27.5 % loading-2017 MW power demand

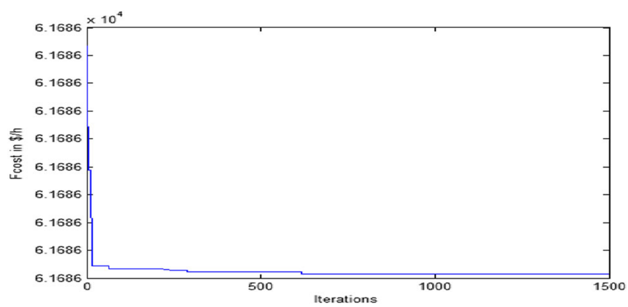

Fig. 9 Fuel cost by GA under 30 % loading-2201 MW power demand

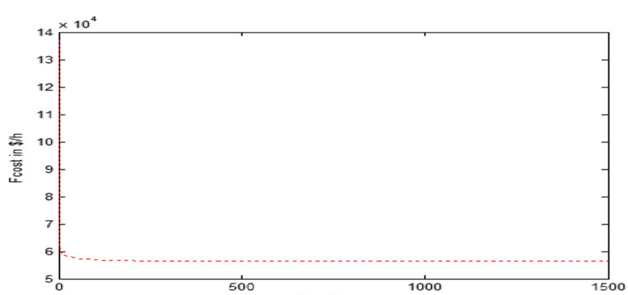

Fig. 10 Fuel cost by TLBO algorithm under 30 % loading-2201 MW power demand

conventional TLBO algorithm has 1000 iterations because of reaching of their optimum F_{cost} values in the proposed algorithm. Total iteration number for the proposed algorithm

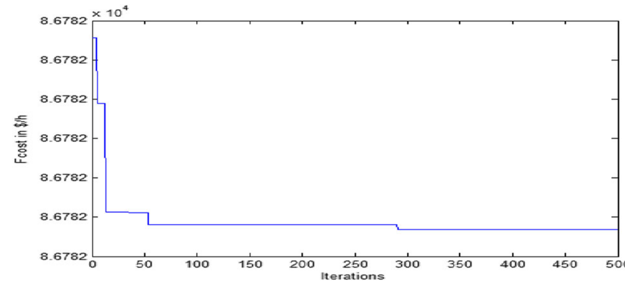

Fig. 11 Genetic section of the proposed algorithm under 30 % loading-2201 MW power demand

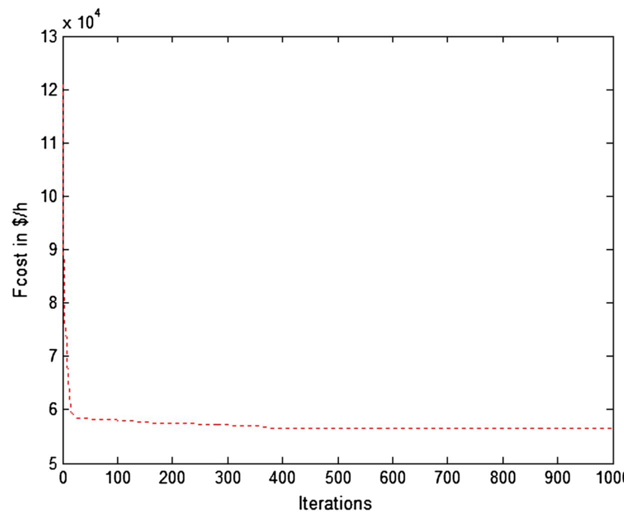

Fig. 12 TLBO algorithm section of the proposed algorithm under 30 % loading-2201 MW power demand

is selected as 1500 to assess the time and cost efficiency of compared algorithms sufficiently.

Three loading situations are taken into consideration. These are 25, 27.5 and 30 % loading, respectively. Conventional GA, TLBO algorithm and the proposed algorithm were executed at each loading condition for totally 1500 iterations.

Two performance criteria were selected in the simulations. The fuel cost graphs were first plotted with Matlab 2011b-Simulink software. Here, fuel costs versus iteration numbers were compared against each other. Fuel costs for different loading situations at analysing of conventional GA, conventional TLBO algorithm and the GA and TLBO sections of the proposed algorithm are shown in Figs. 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12. Second, algorithm run times versus iteration number for different loading conditions are also calculated. The comparison results are provided in Table 2.

Table 2 shows fuel costs and algorithm run time results of three algorithms in terms of loading percentage or related powers and calculations of fuel cost savings of the proposed algorithm compared to other algorithms hourly and totally for 40 years. GA has completed the process in a very short

Table 2 Comparison of three algorithms in terms of fuel cost, algorithm run time for 1500 runs and savings

Loading-power demanded (MW)	Optimization method	Fuel Cost ($/h)	Algorithm run time (s)	Fuel cost saving hourly ($)	Total saving 40 years ($) (350,400 h)
25–1834 %	Genetic algorithm	55,593.51	11.77	2865.26	1,003,987,104
	TLBO algorithm	52,732.66	206.75	4.41	1,545,264
	The proposed algorithm	52,728.25	138.00	–	–
27.5–2017 %	Genetic algorithm	57,850.98	12.37	3386.11	1,186,492,944
	TLBO algorithm	54,473.89	211.95	9.02	3,160,608
	The proposed algorithm	54,464.87	141.86	–	–
30–2201 %	Genetic algorithm	61,686.24	12.04	5239.75	1,836,008,400
	TLBO algorithm	56,447.31	211.12	0.82	287,328
	The proposed algorithm	56,446.49	138.38	–	–

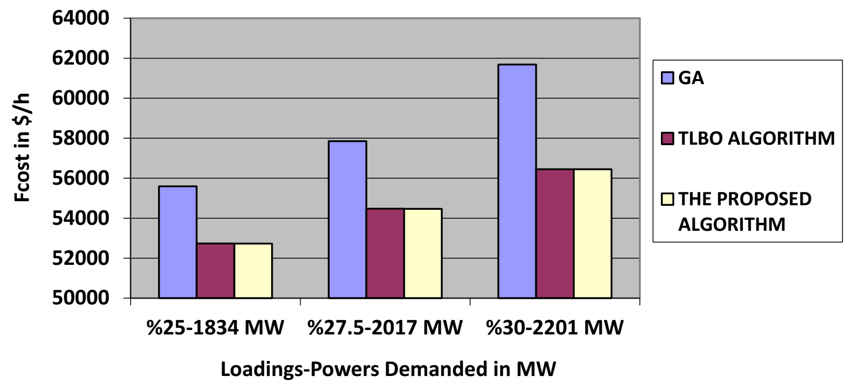

Fig. 13 Fuel cost results of three algorithms under different loadings or power demands

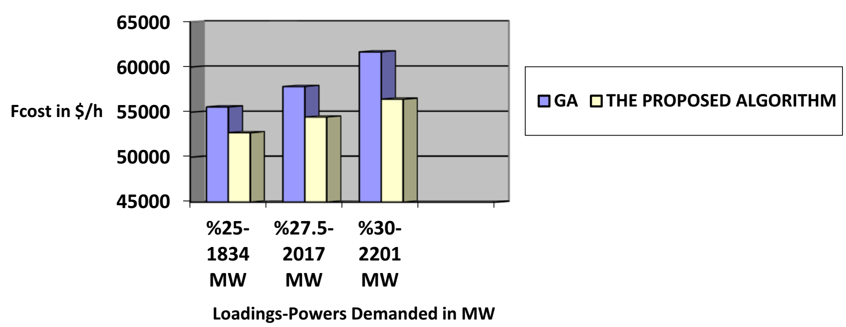

Fig. 14 Fuel cost results of GA and the proposed algorithm under different loadings or power demands

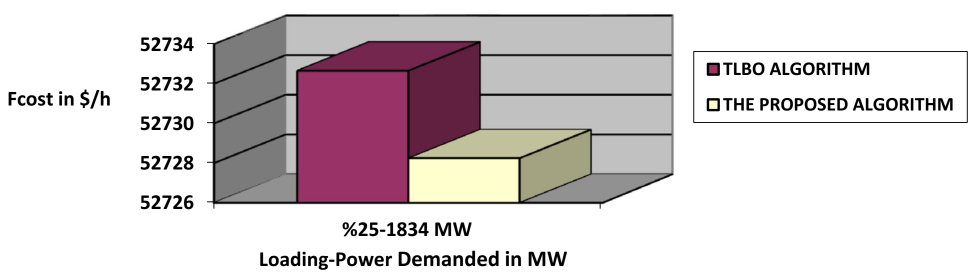

Fig. 15 Fuel cost results of TLBO and the proposed algorithm under 25 % loading or 1834 MW power demand

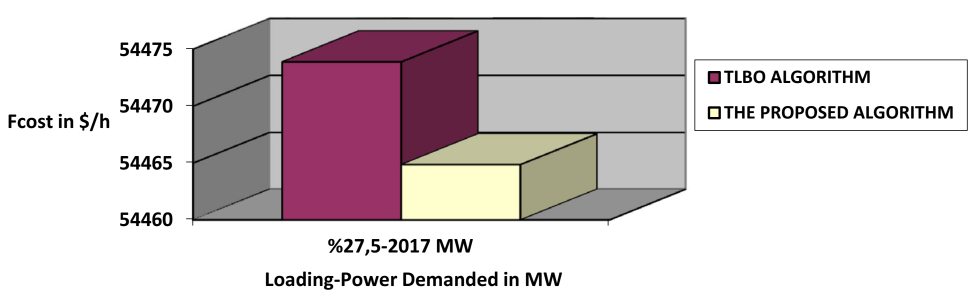

Fig. 16 Fuel cost results of TLBO and the proposed algorithm under 27.5 % loading or 2017 MW power demand

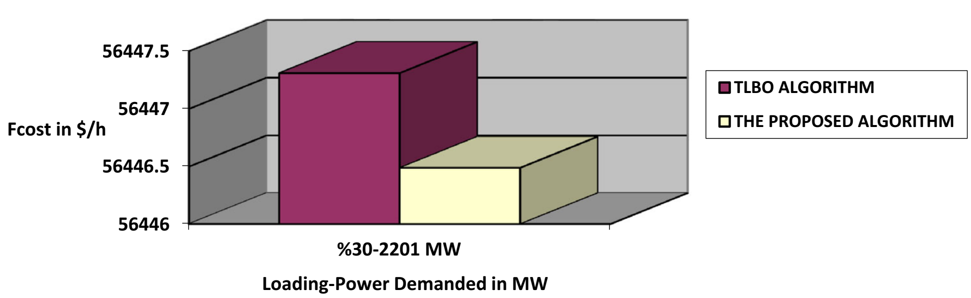

Fig. 17 Fuel cost results of TLBO and the proposed algorithm under 30 % loading or 2201 MW power demand

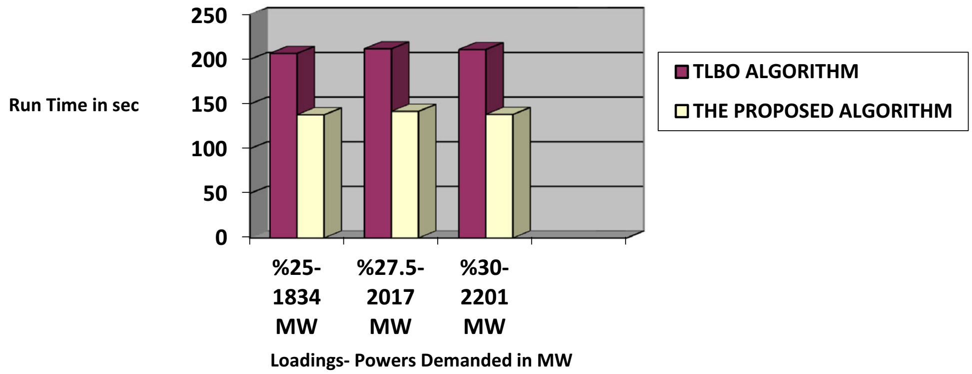

Fig. 18 Algorithm run time results of TLBO and the proposed algorithm under different loadings or power demands

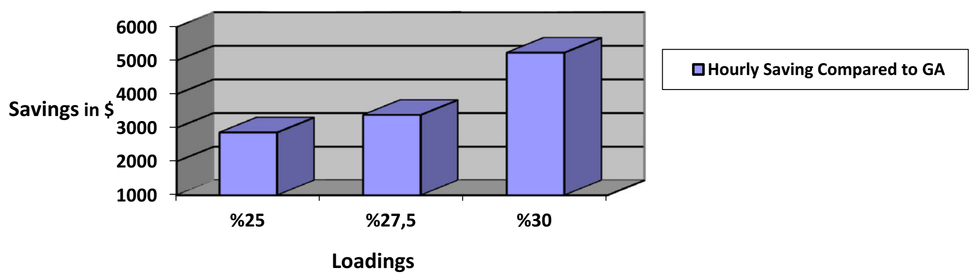

Fig. 19 Hourly saving of the proposed algorithm compared to GA under different loadings

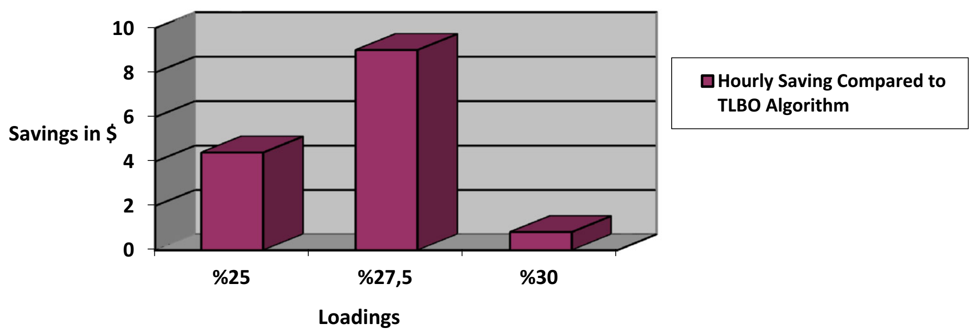

Fig. 20 Hourly saving of the proposed algorithm compared to TLBO algorithm under different loadings

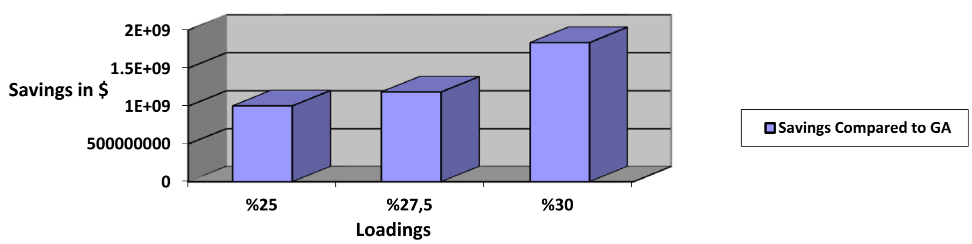

Fig. 21 Savings of the proposed algorithm in 40 years compared to GA under different loadings

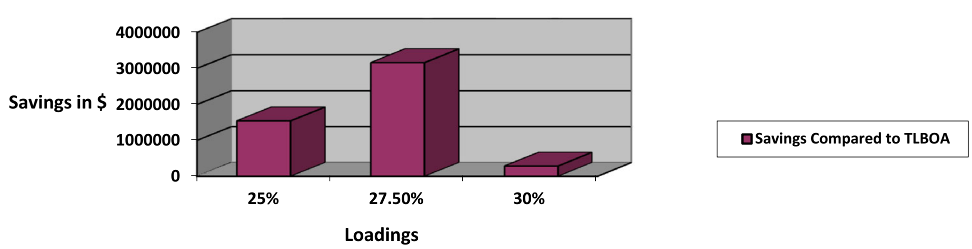

Fig. 22 Savings of the proposed algorithm in 40 years compared to TLBO algorithm under different loadings

time but the fuel cost results obtained are worse than the best fuel cost results calculated by conventional TLBO and the proposed algorithms. Hence, in the proposed algorithm, GA is only used to provide better power values to conventional TLBO algorithm. GA provides the speed to the proposed algorithm by its efficiency at global minimum points.

In Fig. 13, TLBO and the proposed algorithms seem like the same but there is a scale effect. In Fig. 14, fuel cost results of GA and the proposed algorithm under different loadings or power demands are given. For the scale effect in Fig. 13, the fuel cost graphs of Figs. 15, 16, 17 were also drawn between two algorithms separately to see the effectiveness of the proposed algorithm on fuel cost, algorithm run time and economic savings.

In Fig. 18, TLBO and the proposed algorithm run time results are given. Here, GA result does not take into consideration because GA fuel cost result is out of the optimization aims and an unacceptable outcome economically. In Fig. 18, the proposed algorithm supplies 68.75, 70.09, 72.74 s algorithm run time saving according to TLBO algorithm for the 25, 27,5, 30 % loading cases, respectively.

In Figs. 19, 20, 21, 22, the savings provided using the proposed algorithm are shown hourly and for 40 years for a comparison. In Fig. 19, the proposed algorithm supplies 2865.26 $, 3386.11 $, 5239.75 $ savings hourly according to GA for the 25, 27.5, 30 % loading cases, respectively.

In Fig. 20, the proposed algorithm supplies 4,41 $, 9,02 $, 0,82 $ savings hourly according to TLBO algorithm for the 25, 27.5, 30 % loading cases, respectively.

In Fig. 21, the proposed algorithm supplies 1,003,987,104 $, 1,186,492,944 $, 1,836,008,400 $ savings in 40 years according to GA for the 25, 27.5, 30 % loading cases, respectively.

In Fig. 22, the proposed algorithm supplies 1,545,264 $, 3,160,608 $, 287,328 $ savings in 40 years according to TLBO algorithm for the 25, 27.5, 30 % loading cases, respectively.

Performance comparison of the proposed algorithm versus remaining indicates that the elapsed time with the proposed algorithm has a quite shorter run time and better results at fuel cost after multiple trials. The proposed algorithm shows a better performance in wider intervals of generator power values particularly. That is also suitable for the frequency stability in interconnected electric power systems. Simulations have been repeated for many attempts and a success has obtained for all. As iteration number is gradually increased, fuel cost results converges to each other by the algorithms but the proposed algorithm also shows a great performance for the algorithm run time comparison.

The proposed algorithm seems to be more advantageous than the others fulfilling the demand for 19 bus thermal wind-powered hybrid energy generation system.

6 Conclusions

In this paper, a proposed hybrid genetic teaching learning-based (G-TLBO) algorithm was applied and tested on a part of Turkish electrical network which consists of wind- and thermal-powered 19 bus active generation system under constraints.

In the proposed algorithm, genetic algorithm section has a difference value (d_v) between 10 and 1100 and a multiplier value m_v between 1 and 50 to decrease the algorithm run time and the fuel cost. GA and d_v values are working together to provide the best students to conventional TLBO algorithm. The conventional genetic and TLBO algorithms and d_v difference value are working at a close interaction, so that the whole algorithm performance was improved at fuel cost and algorithm run time.

The proposed algorithm especially shows a great performance in terms of algorithm run time at every loading condition. It has been therefore shown that the proposed algorithm is effective and provides significant improvement in hybrid energy generation system performance. The proposed method is also suitable for a large-scale energy generation structures.

As the capacity of energy generation units has increased by adding new renewable energy sources to the interconnected energy generation system, the proposed algorithm will gain much more importance.

Additionally, countries which have an installed power system such as Turkey, as it can be seen from the Figs. 21 and 22 above, the proposed method provides great savings. Therefore, the proposed method is suggested from this point of view.

In conclusion, the proposed algorithm is recommended to implement in power flow analysis and power flow control applications in large- scale because of its fuel cost and time efficiency.

Compliance with ethical standards

Conflict of interest The authors declare that they have no conflict of interest.

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