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A new hybrid gravitational search-teaching-learning-based optimization method for the solution of economic dispatch of power systems

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Abstract: The economic dispatch problem (EDP) is a complex, constrained, and nonlinear optimization problem. In the EDP, the active power bus should operate between the minimum and maximum bus limits to minimize the fuel cost. In this study, a fast, efficient, and reliable hybrid gravitational search algorithm-teaching learning based optimization (GSA-TLBO) method was proposed for the purpose of solving the EDP in power systems. The proposed method separates the search space into two sections as global and local searching. In the first part, searching was carried out by GSA method effectively to form the second search space. In the second part, the optimum solution was sought in the local search space by the TLBO method. The proposed method was implemented to a constrained benchmark G01 problem. The proposed hybrid method was then applied to the constrained EDP in IEEE 30-bus and IEEE 57-bus test systems and Turkey's 22-bus power system to minimize the fuel cost. Obtained results were compared with other methods. Experimental results show that the proposed method results in shorter, more reliable, and efficient lowest fuel cost solutions. It has been found that the proposed method can be used to solve constrained optimization problems.

Key words: Hybrid optimization method, gravitational search algorithm, teaching-learning-based optimization algorithm, economic dispatch, power systems

1. Introduction

Economic dispatch is known as the requirement of the generation units to meet the demand load in a power system at a minimum cost [1]. The economic dispatch problem (EDP) is a nonlinear, constrained, multiple local optimal point optimization problem for power system management and planning [2,3]. To solve this problem, traditional methods such as Newton's method [4], the Gauss–Seidel method [5], and linear and quadratic programming techniques [6] are used. However, solutions of these traditional methods are far from optimal for large-scale systems [2,3,7–10]. Therefore, heuristic optimization methods based on artificial intelligence-based techniques been used for closer, more effective, and faster solutions of the EDP to the optimum result [3,7,11].

Some of the intuitive metaheuristic optimization methods used in EDP solutions are the genetic algorithm (GA) [11], particle swarm optimization (PSO) [2], artificial bee colony (ABC) [12,13], gravitation search algorithm (GSA) [14], and teaching-learning-based optimization (TLBO) [15]. Even if these methods solve the EDP, basically, they do not easily recover from the long computation time and the problem of sticking to the local optimum [3,7]. Hence, hybrid methods are obtained by combining the points where the heuristic algorithms are strong and the EDP is applied. In this way, effective solutions can be found to reach the minimum fuel cost quickly without getting to the local optimum.

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In order to minimize the fuel cost in the EDP, the work performed by hybrid methods is as follows: the hybrid FAPSO-NM method with combinations of fuzzy adaptive (FA), PSO algorithm, and Nelder–Mead (NM) methods [8]; the G-TLBO algorithm combined with GA and TLBO algorithms [10]; simulated annealing with shuffle frog leaping algorithm (SFLA-SA) method [16]; ABCGLN method modifying the ABC global and local neighborhoods [17]; hybrid MICA-TLA with combinations of the modified imperialist competitive algorithm (MICA) and teaching learning algorithm [18] and CMICA [19]; the EADE hybrid method, which is a combination of evolving ant direction search with DE algorithm [20]; and the FHSA method, an integration of fuzzy logic system and harmony search (HS) algorithm [21].

In this study, a hybrid algorithm of gravitational search algorithm with teaching-learning-based optimization (GSA-TLBO) was proposed and implemented in order to avoid local minima by using fewer iterations for the EDP solution. The GSA is a physics-based heuristic optimization algorithm that takes Newton's gravity and motion laws as a basic principle [22]. The GSA has an easy execution structure that can perform global searches [23]. TLBO is a social-based heuristic optimization algorithm that is inspired by the interaction of students and teachers in a classroom [24]. TLBO can provide successful solutions with parameter-free, less computationally intensive solutions to large-scale optimization problems [23]. Hence, the search space is defined in two ways as global search and local search. The GSA's successful calculation method in global search space and TLBO's effective search feature in local search space are combined [25].

The proposed method was first tested with the solution of the constrained G01 benchmark function. It was then applied to the EDP solution of power systems. These power systems are IEEE 30- and IEEE 57-bus test systems, which are well-known, thermal-constrained test systems used for the minimum fuel cost solution by standard or newly developed optimization algorithms. In addition, there are local power systems such as Turkey's 22-bus power system [26]. The total installed power of Turkey was 31,846 MW in 2002, whereas it was 78,497 MW in 2016. In 2016, 57% of Turkey's installed power was based on fossil fuel-based thermal power systems [27]. The rapid depletion of fossil fuels and the fact that Turkey imports these fuels increases the cost of electricity generation. Therefore, it is very important to operate the 22-bus Turkish power system with minimum economic cost. Despite some studies on Turkey's 22-bus power system [10,13,28], there are few EDP calculations using the standard and newly developed optimization algorithms. Obtained bus test results were compared with the results of other methods in the literature.

2. Materials and methods

2.1. GSA

A physics-based metaheuristic optimization algorithm depending on Newton's laws was proposed by Rashidi et al. and called GSA [22]. This algorithm has masses in the search space. These masses are defined as agents. According to Newton's law of gravity, larger masses attract small masses around them. In the search space, masses are attracted to the force that is caused by a mass that is large. The gravitational force between these masses determines the best result in the search space.

2.2. TLBO

The TLBO algorithm was proposed by Rao et al. [24]. The algorithm is a population-based heuristic and inspired by the behavior of students and teachers in a classroom [24]. The algorithm starts with the creation of random students in a class to provide the best learning by interacting with the students themselves and their teachers. The one who can learn the best in class learns as much as a teacher, and so the more the teacher trains, the more successful the learning will be. The TLBO algorithm has two parts, namely student and teacher phases.

2.3. The proposed method (hybrid GSA-TLBO)

Hybrid algorithms are achieved by combining powerful global or local search features of at least two heuristic algorithms to find the best solution with fewer iterations to solve a given problem [29].

In hybrid approaches, the main purposes are to achieve better optimization results, faster similar optimization results, and faster and better optimization results by the combination of methods such as global search, local search, convergence rate, and insensitivity to initial conditions [30]. In accordance with these objectives, the hybrid method called global-local search hybrids [31,32], in which one of the heuristic algorithms searches globally and the other locally, was used in this study to combine the standard GSA and TLBO.

In this study, for the solution of the constrained optimization problem, a new hybrid method is proposed by taking the strengths of global search and local search features of the standard GSA and TLBO algorithms. Despite the GSA's success in global search, its search efficiency and resolution accuracy need to be improved [23,25]. TLBO provides good performance with fewer computations in solving large-scale optimization problems [23,25,33]. Therefore the aim is to narrow the solution space by performing a global search with the GSA to get the best solution and to proceed to the result with the TLBO, which searches effectively in this second search space [25]. This can be thought of as an increase in educational achievement in a class that is formed by successful teachers and well-selected learners in real life. With the hybrid method proposed, it is aimed to reach the global optimal result with the least number of iterations and to get rid of attachment to the local search area [10,25,29,34]. In Figure 1, a multimodal function with a large number of local minimum points and one global minimum point is given.

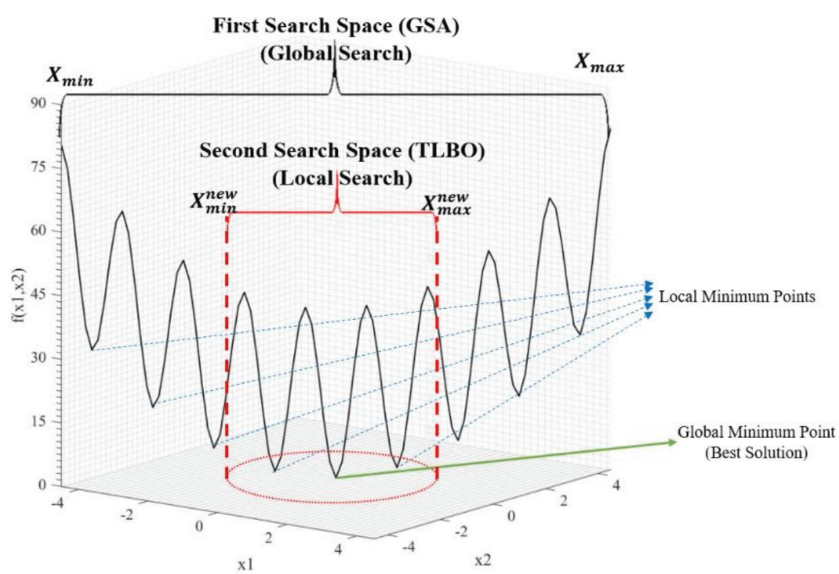

Figure 1. Graphical representation of the proposed method.

In Figure 1, the standard GSA method (X_{min}, X_{max}) is applied to the objective function in the first search space created by the initial values. This phase is the global search phase. The second search space is formed by the values of GSA X_{GSA}^{best} and (X_{min}^{new}, X_{max}^{new}) initial TLBO in accordance with the steps of the proposed method, as shown in Figure 2 [25]. This phase is the local search phase.

for $i = 1{:}\,dim$ // dim: the number of dimension or the size of design variable number

$X_{max}^{new}(i) = X_{GSA}^{best}(i) + (rand)(X_{max} - X_{GSA}^{best}(i))$;

$X_{min}^{new}(i) = X_{GSA}^{best}(i) + (rand)(X_{min} - X_{GSA}^{best}(i))$;

if ($X_{max}^{new}(i) > X_{max}$)

$X_{max}^{new}(i) = X_{max}$;

end

if ($X_{min}^{new}(i) < X_{min}$)

$X_{min}^{new}(i) = X_{min}$;

end

end

Figure 2. The pseudocode that determines the initial value according to the dimensions of the second search space [25].

The proposed method has been applied for the solution of the G01 benchmark test function problem. The G01 is a quadratic minimization problem with 13 design variables and 9 linear inequality constraints [35]. In Eq. (1), the objective function is given, and inequality constraints are given from Eq. (2) to Eq. (10). In this problem, the ratio of the appropriate search area to the entire search area is about 0.0003% [36] and at the optimum point there are 6 active restrictions ($g_1, g_2, g_3, g_7, g_8, g_9$). The best solution for the G01 problem is $x^* = (1, 1, 1, 1, 1, 1, 1, 1, 1, 3, 3, 3, 1)$ and the global minimum function value $f(x^*) = -15$ [35].

$$Minimize\, f(x) = 5\sum_{i=1}^{4} x_i 5 \sum_{i=1}^{4} x_i^2 \sum_{i=5}^{13} x_i \tag{1}$$

subject to:

$$g_1(x) = 2x_1 + 2x_2 + x_{10} + x_{11} \leq 0 \tag{2}$$

$$g_2(x) = 2x_1 + 2x_3 + x_{10} + x_{12} \leq 0 \tag{3}$$

$$g_3(x) = 2x_2 + 2x_3 + x_{11} + x_{12} \leq 0 \tag{4}$$

$$g_4(x) = 8x_1 + x_{10} \leq 0 \tag{5}$$

$$g_5(x) = 8x_2 + x_{11} \leq 0 \tag{6}$$

$$g_6(x) = 8x_3 + x_{12} \leq 0 \tag{7}$$

$$g_7(x) = 2x_4x_5 + x_{10} \leq 0 \tag{8}$$

$$g_8(x) = 2x_6x_7 + x_{11} \leq 0 \tag{9}$$

$$g_9(x) = 2x_8x_9 + x_{12} \leq 0 \tag{10}$$

Here, the bounds are $0 \leq x_i \leq 1$ $(i = 1, \ldots, 9)$, $0 \leq x_i \leq 100$ $(i = 10, 11, 12)$, and $0 \leq x_{13} \leq 1$.

The standard GSA, TLBO, and the proposed method are applied to solve this problem according to the parameters given in Table 1. All algorithms were run 30 times and calculations were made for the minimum value of the function. The proposed method entails the initial limit values for the first search space $X_{min} = (0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,)$ and $X_{max} = (1, 1, 1, 1, 1, 1, 1, 1, 1, 100, 100, 100, 1)$. At the end of this stage, the value $f(x)$ is the minimum value for the solution X_{GSA}^{best} best values as given in Table 2. The pseudocodes in Figure 2 and the second search space TLBO initial limit values are determined as in Table 2. After the proposed method satisfies the stopping criterion, it yields a value close to the global minimum or global minimum that it finds. According to the best results of the method proposed in Table 2, X values and $f(x)$ function values are given. With the proposed method, the second search space is created in order to get out of the local minimum area in which the GSA is installed in the first search space and the global minimum value is calculated by TLBO. In order to solve the constrained optimization problems in this way, the GSA's search efficiency and solution-precision disadvantages were solved by combining TLBO with a second search space. In this way, it is concentrated on an explicit subregion of the search space [37]. At the end of the first search space in Table 2, the GSA found the best value of –3. New search space limits for the value of X_{GSA}^{best} were determined and TLBO was run outside the area where the GSA was installed in the local minimums and the proposed method calculated the minimum value of $f(x)$ as –14.99322. In Table 3, the statistical analysis of the GSA, TLBO, and the proposed method is given for the G01 problem solution. Figure 3 shows the convergence curve of the G01 problem for the solution of the GSA, TLBO, and the proposed method. In Algorithm 1, the algorithmic table of the GSA [22,25] in the first search space, in Algorithm 2, the algorithmic table for determining the second search space boundaries [25], and in Algorithm 3, TLBO's [24,25] algorithmic tables in the second search space are given.

Table 1. Initial algorithm parameters for the standard GSA, TLBO, and the proposed method.

Algorithm	Parameter	Value
GSA	Population (mass) number	50
	G_0 (gravitational constant)	20
	α (user-specified constant)	100
	Number of dimensions	Number of design variables
	Number of iterations	100
TLBO	Population number	50
	Number of dimensions	Number of design variables
	Number of iterations	100
The proposed method	Population number	GSA: 25, TLBO: 25
	G_0 (gravitational constant)	20
	α (user-specified constant)	100
	Number of dimensions	Number of design variables
	Number of iterations	100

2.4. EDP formulation

The EDP is a nonlinear optimization problem that minimizes the cost of fuel, which is the objective function, under equality and inequality constraints. In general, the mathematical form of the EDP can be expressed as in Eqs. (11) to (13).

Table 2. The best solution of the proposed method for the G01 problem.

Design variable	First search space (GSA)			Second search space (TLBO)		The proposed method
	X_{min}	X_{max}	X_{GSA}^{best}	X_{min}^{new}	X_{max}^{new}	X
X_1	0	1	1	0.646162	1	0.999965
X_2	0	1	1	0.456174	1	0.999995
X_3	0	1	1	0.302760	1	1
X_4	0	1	1	0.927032	1	0.999828
X_5	0	1	0	0	1	0.999761
X_6	0	1	1	0.724346	1	0.999498
X_7	0	1	0	0	1	0.999497
X_8	0	1	1	0.912138	1	0.999971
X_9	0	1	0	0	1	0.999954
X_{10}	0	100	0	0	22.65689	2.998686
X_{11}	0	100	0	0	13.43876	2.998106
X_{12}	0	100	0	0	9.61754	2.998811
X_{13}	0	1	1	0.859965	1	0.999995
$f(X)$			–3			–14.99322

Table 3. Statistical comparison of standard GSA, TLBO, and the proposed method for the G01 problem solution.

Methods	Solution values of $f(x)$			
	Best	Mean	Worst	SD
The proposed method	–14.99322	–10.75462	–3.052701	0.84854
GSA	–5.73319	2.669155	10.91462	14.52493
TLBO	–8.97775	–3.221374	–0.36271	1.97995

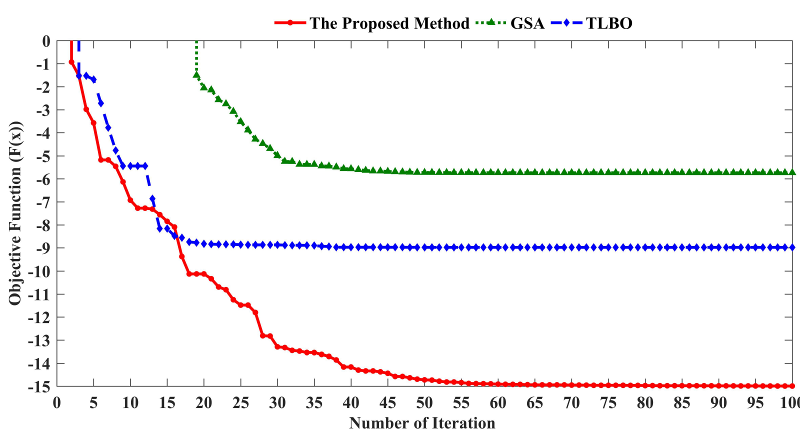

Figure 3. Variation of the G01 problem solution of the objective function with the number of iterations.

$$minimize \quad F(x) \tag{11}$$

$$subject\,to \quad g\,(x) = 0 \tag{12}$$

Algorithm 1 GSA (first search space) [22,25].

Step

1: Inputs: Enter the standard GSA, TLBO parameters, and X_{min} and X_{max} limit values and maximum iteration number (max_iter).

Output: Get the results of the GSA.

2: $X_i = (x_i^1, \ldots, x_i^d, \ldots, x_i^N)$ // *for* $i = 1, 2, \ldots, N$

//Determine N objects (agents) randomly as the number of every design variable.

//Where x_i^d *presents the position of* i*th agent in the* d*th dimension*

3: Let **iter = 1**

4: Apply objective function for every object (agent)

5: **for** i = *1* **to** N

6: **Update** $G_i(t) = G_i(G_0 t)$; // $G_0(t)$ *is the value of the gravitational constant*

7: **Update** $m_i(t) = \frac{fit_i(t)\ worst(t)}{best(t)\ worst(t)}$; // $fit_i(t)$ *represents the objective function value of*

//agent i *at time* t

8: **Update** $M_i(t) = \frac{m_i(t)}{\sum_{j=1}^{N} m_j(t)}$; // $M_i(t)$ *is the inertial mass of* i*th agent*

9: **end for**

10: $F_i^d(t) = \sum_{j=1,\, j \neq i}^{N} rand_j F_{ij}^d(t)$; // *Calculation of the total force in different directions*

11: $a_i^d(t) = \frac{F_i^d(t)}{M_{ii}(t)}$; // *Calculation of the acceleration*

12: $v_i^d(t+1) = rand_i v_i^d(t) + a_i^d(t)$; // *Calculation of the velocity*

13: $x_i^d(t+1) = x_i^d(t) + v_i^d(t+1)$; // *Updating agents' positions*

14: **iter = iter + 1**

15: **if** $iter <= max\_iter$

16: Step 4 is carried out

17: **else**

18: X_{GSA}^{best} is taken as the result of GSA.

19: **end if**

20: Terminate GSA and carry out Step 21.

$$h(x) \leq 0 \tag{13}$$

Here, in Eq. (11), $F(x)$ is the objective function; in Eq. (12), $g(x)$ is the equality constraints; and in Eq. (13), $h(x)$ is the inequality constraints. x is a variable that defines the generator active powers used as control variables in the EDP. The main aim of the EDP is minimizing the fuel cost and it can be given as in Eq. (14) [38,39].

$$\text{minimize } F(x) = \sum_{i=1}^{N_G} \left(a_i P_i^2 + b_i P_i + c_i \right) \quad (\$/h) \tag{14}$$

Algorithm 2 Determine the new search space [25].

Step Input: Get the results of the GSA.

Output: Determine the TLBO search space limits.

for *i=1* **to dim** *// dim: the number of dimensions or the design*

$X_{max}^{new}(i) = X_{GSA}^{best}(i) + (rand_i)\left(X_{max}(i)\, X_{GSA}^{best}(i)\right);$

//determine the new maximum limit search.

$X_{min}^{new}(i) = X_{GSA}^{best}(i) + (rand_i)\left(X_{min}(i)\, X_{GSA}^{best}(i)\right);$

//determine the new minimum limit search

if $(X_{max}^{new}(i) > X_{max}(i))$ *// if the maximum limit value is exceeded.*

$X_{max}^{new}(i) = X_{max}(i);$

end if

if $(X_{min}^{new}(i) < X_{min}(i))$ *// if the minimum limit value is exceeded.*

$X_{min}^{new}(i) = X_{min}(i);$

end if

end for

Step 31 is carried out.

Subject to

$$\sum_{i=1}^{N_G} P_i\, P_D P_L = 0 \tag{15}$$

$$P_L = \sum_{i=1}^{N_G}\sum_{j=1}^{N_G} P_i B_{ij} P_j + \sum_{i=1}^{N_G} P_i B_{0i} + B_{00} \tag{16}$$

$$P_i^{min} \leq P_i \leq P_i^{max} 1 \leq i \leq N_G \tag{17}$$

In Eq. (14), F is the fuel cost function of the power system, N_G is generator bus number, P_i is the generation output of the active generating bus i, and a_i, b_i, and c_i are the cost fuel coefficients of generating bus i. Eq. (15) gives equality constraints between the total power of the system and the total system loads P_D and losses P_L. In Eq. (16), the loss P_L is calculated by the B_{ij}, B_{0i}, and B_{00} loss coefficients. In Eq. (17), the lower limit (P_i^{min}) and the upper limit (P_i^{max}) inequality constraints of each active power are given. The minimum fuel cost is calculated under these conditions.

2.5. Application of the proposed method to the EDP

The proposed method was applied to minimize the fuel cost in the EDP. The flowchart of the proposed hybrid GSA-TLBO algorithm for the EDP solution is given in Figure 4. The application steps of the proposed method for the EDP solution are given in Algorithm 4.

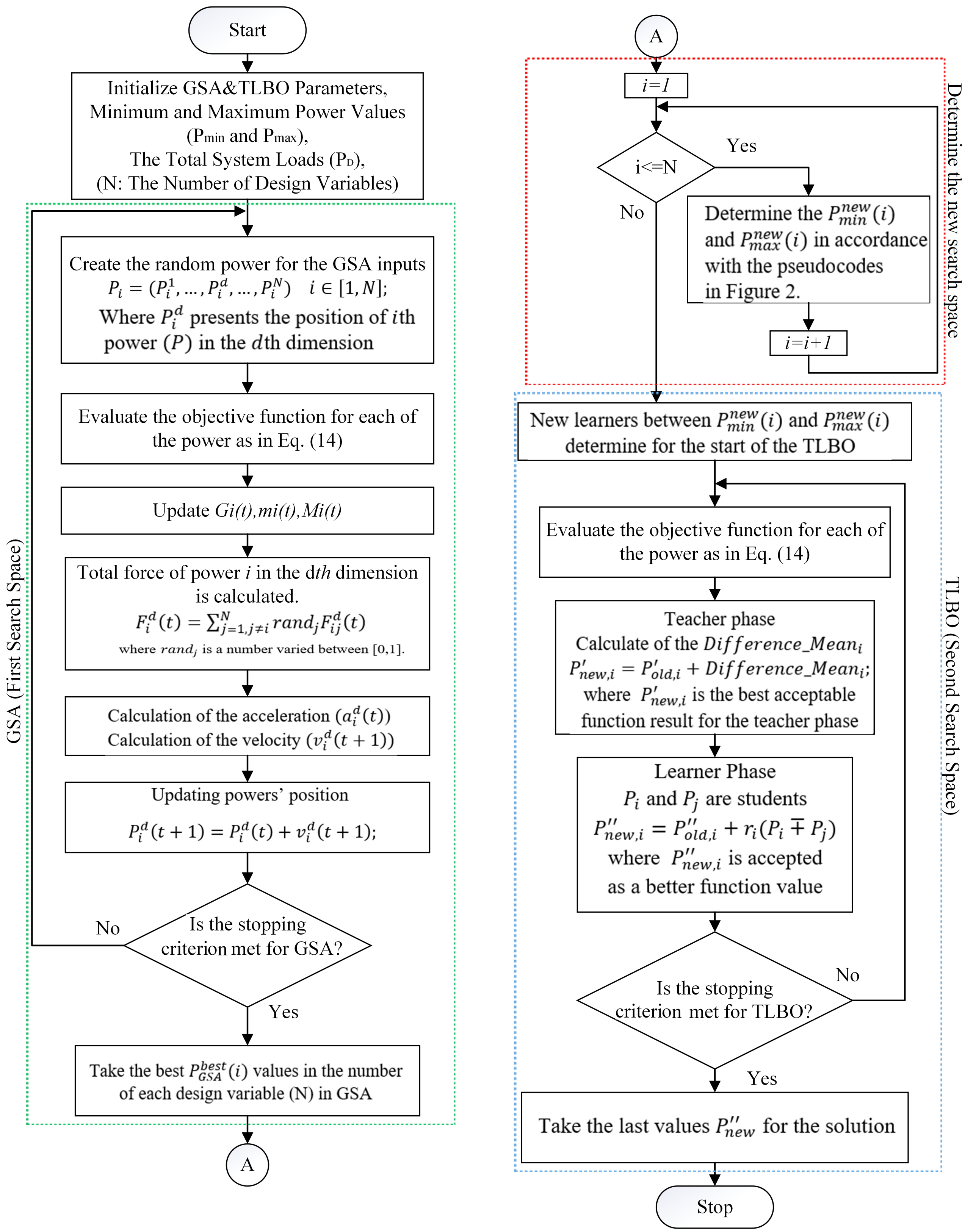

Figure 4. Flowchart of the proposed method for the EDP solution.

Algorithm 3 TLBO (second search space) [24,25].

Step Input: $X_{min}^{new}(i)$ and $X_{max}^{new}(i)$ limit values.
 Output: Get the best results and values.

```
Determine the TLBO search space between the X_min^new(i) and X_max^new(i) limits.
    Create the learner population (P_n) randomly, which is composed of every design variable.
Let gen = 1
Apply the objective function for every learner.
Teacher phase:
Difference_Mean_i = r_i (M_new,i T_F M_i) ; // There is a mean value between teacher and
//student learning levels
T_F = round[1 + rand(0,1)] ; // (T_F value can be 1 or 2)
// The value of T_F is decided randomly with equal probability
X'_new,i = X'_old,i + Difference_Mean_i; // The existing solution is updated in the teacher
// phase. Here, X'_new,i, is the updated value of X'_old,i and it is the best acceptable function result for the
//teacher phase.
The best function values of the teacher phase are kept in memory to use them as inputs in the learner phase.
Learner Phase:
for i = 1 to P_n // randomly select two learners X''_i and X''_j, where i ≠ j,
        if f(X''_i) < f(X''_j)
            X''_new,i = X''_old,i + r_i(X''_i X''_j)
        else
            X''_new,i = X''_old,i + r_i(X''_j X''_i)
        end if
end for
Accept X''_new if it gives a better function value.
gen = gen + 1
if gen <= max?_iter
Step 33 is carried out.
else
Stop if the maximum generation number is achieved.
end if
```

2.6. Comparative test results of the power systems

In the analyses, the proposed method, the standard GSA [22], and TLBO [24] are compared and all the experiments are implemented using the i7-6700HQ 2.6 GHz CPU, 8 GB memory, on a Windows 10 operating system with the MATLAB R-2015b program.

The standard GSA, TLBO, and the proposed method with the parameters in Table 1 were applied to the IEEE 30-bus and IEEE 57-bus test systems and Turkey's 22-bus power system. The number of design variables in Table 1 are the active power buses and these are 6, 7, and 8 for the IEEE 30-bus, IEEE 57-bus, and Turkey's

Algorithm 4 Application of the proposed method for the EDP solution.

Step

1: Inputs: Enter the standard GSA and TLBO input parameters. Enter the minimum and maximum power values, constraints, demanded power values for each generator, and maximum iteration number (max_iter).
  Output: Get the generator power value (MW), fuel cost ($\$/h$), and power loss ($MW$) of each generator.
2: Apply the GSA for the first search space as in **Algorithm 1**.
3: Determine the random masses between the power limits for the GSA start.
4: Evaluate the objective function for each of the masses as in Eq. (14).
5: Calculate the gravitational constant $G(t)$ and update the $best(t)$ and $worst(t)$ for the population for t moment.
6: Calculate the total force $F(t)$ for each mass.
7: For each mass, calculate the acceleration (a).
8: Update the velocity and position.
9: Take the mass value as P_{GSA}^{best}, which has the best position for the solution.
10: Go to Step 4 until the stop criterion is met. Otherwise, go to Step 11.
11: Apply **Algorithm 2** for the new search space and determine the new power values.
12: Calculate the power values that the GSA calculates for each active power bus, as in Figure 2, and set the second search space for TLBO as $P_{min}^{new}(i)$ and $P_{max}^{new}(i)$.
13: Apply the TLBO for the second space as in **Algorithm 3**.
14: Create a random population between $P_{min}^{new}(i)$ and $P_{max}^{new}(i)$.
15: Calculate the objective function in Eq. (14) for each population.
16: Calculate $Difference\_Mean$ at teacher phase.
17: Create $P_{new,i}^{'}$, the best teacher in each class.
18: Create $P_{new,i}^{''}$ at learner phase.
19: Go to Step 15 until the stopping criterion is met. Otherwise, go to Step 20.
20: Get the best solution $P_{new,i}^{''}$
21: End

22-bus power systems, respectively. The obtained results for comparison are given with the following tables and graphs.

3. IEEE 30-bus test system and results obtained

The IEEE 30-bus test system includes 41 transmission lines, 4 transformers, 2 shunt reactors, and 6 generator buses with numbers 1, 2, 5, 8, 11, and 13 [9,39,40]. In this test system, the power base value is taken as 100 MVA and the active power demand is 283.4 MW. The data of the IEEE 30-bus test system are taken from [39].

The proposed method was applied to the IEEE 30-bus test system. In order to minimize the total fuel cost, the algorithm was tested in 30 independent runs. In order to calculate the minimum fuel cost of the system in this way, the active power values of each generator unit and the lost power value of the system are given in Table 4 for comparison. Values not in tables are given as N/A (not applicable).

With the proposed method, the fuel cost of the IEEE 30-bus test was found to be 798.609127 \$/h as the minimum, 799.1081576 \$/h as an average, and 799.502821 \$/h as the maximum, respectively, and these results are compared with other studies in Table 5. The proposed method has found the minimum fuel cost to be lower than the studies in the literature. There is a 0.066016 \$/h difference between the nearest GSA result [14] and the calculated minimum fuel cost by the method proposed in Table 5. This result shows that our proposed method performs accurate or similar calculations in the IEEE 30-bus test system according to the literature.

Table 4. Comparison of power values and minimum fuel cost in the IEEE 30-bus test system between the proposed and other methods.

Variables	The proposed method	GSA [14]	TLBO [15]	PSO [9]	ABC [13]
P_1 (MW)	177.289	175.74982	177.0578	176.96	176.476
P_2 (MW)	52.62845	48.165537	48.6973	48.98	48.907
P_5 (MW)	20.72996	21.381724	21.3044	21.30	22.222
P_8 (MW)	17.82592	21.561405	21.0811	21.19	21.125
P_{11} (MW)	11.32224	12.417360	11.8843	11.97	12.307
P_{13} (MW)	12.18001	12.510199	12.0000	12	12.000
Fuel cost ($\$/h$)	798.609127	798.67514	799.0715	800.41	799.264
Power loss (MW)	8.57558	8.386049	8.6260	(N/A)	(N/A)

At the same time, it is seen that the fuel cost curve of the proposed method in Figure 5 is less convergent and has lower fuel cost than the standard GSA and TLBO algorithms.

Table 5. Statistical comparison of simulation results of the IEEE 30-bus test system with other studies.

Methods	Fuel cost ($\$/h$)			SD	Runtime(s)
	Best	Mean	Worst		
The proposed method	798.609127	799.1081576	799.502821	9.13e-02	9.31643
GSA	799.412553	800.2234687	802.248836	6.1647e-1	11.2587
GSA [14]	798.675143	798.913128	799.028419	N/A	10.7582
TLBO	799.961393	800.4009578	802.127927	4.0274e-1	11.0253
TLBO [15]	799.0715	N/A	N/A	N/A	N/A
PSO [9]	800.41	N/A	N/A	N/A	N/A
ABC [13]	799.264	N/A	N/A	N/A	N/A
ABCGLN [17]	800.4464	800.5607	N/A	N/A	18.0
SFLA-SA[16]	801.79	N/A	N/A	N/A	18.93

3.1. IEEE 57-bus test system and results obtained

The IEEE 57-bus test system is a large power system with seven generators at buses 1, 2, 3, 6, 8, 9, and 12 and 80 transmission lines, 15 transformers, and 3 shunt reactors [40]. In this test system, the power base value is taken as 100 MVA and the active power demand is 1250.8 MW. The data of the IEEE 57-bus test system are taken from [40].

The proposed method has been applied to this system in order to find the minimum fuel cost of the IEEE 57-bus test system. For the experimental study, the algorithm was tested in 30 independent runs and the active power values, the minimum fuel cost, and the lost power values are given in Table 6 for comparison.

With the proposed method, the fuel cost of the IEEE 57-bus test system was found to be a minimum of 41,651.6237 $/h, average of 41,662.0328 $/h, and maximum of 41,700.3861 $/h and these statistical results are compared with other studies in Table 7. The proposed hybrid method calculates the minimum fuel cost to be lower than other methods. The CMICA4 method [19], which is the closest to the minimum fuel cost found by

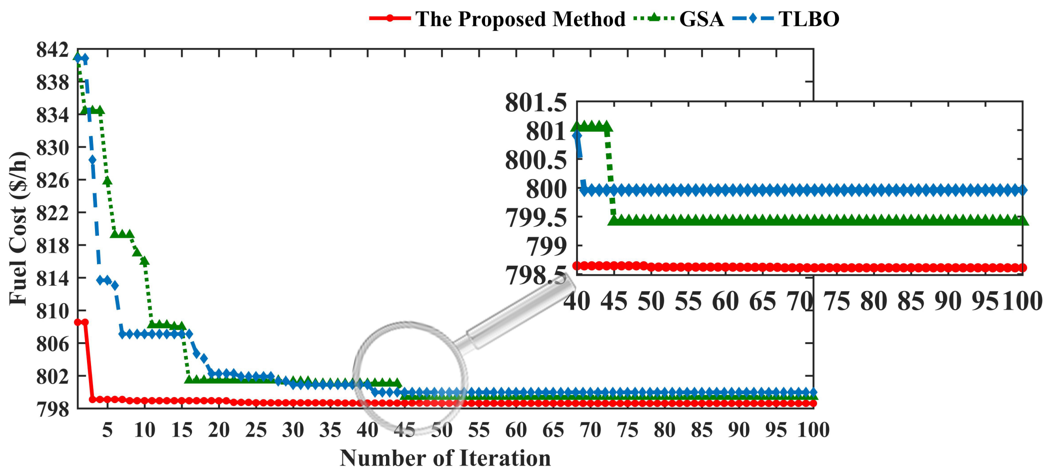

Figure 5. Variation of the fuel cost convergence performance of the proposed method with the number of iterations in the IEEE 30-bus system.

Table 6. Comparison of power values and minimum fuel cost in the IEEE 57-bus test system between the proposed and other methods.

Variables	The proposed method	GSA [14]	TLBO [18]	CMICA4 [19]	ABC [12]
P_1 (MW)	134.2965	142.369	143.53	142.94	142.8106
P_2 (MW)	84.71307	92.63	88.0583	90.3644	90.0328
P_3 (MW)	45.16725	45.318	44.8178	45.0698	44.5147
P_6 (MW)	98.08796	72.355	76.4726	71.7876	74.2003
P_8 (MW)	488.2852	464.743	458.5102	459.2607	454.8475
P_9 (MW)	84.96414	84.999	91.9476	95.6995	96.8847
P_{12} (MW)	330.617	363.951	362.6991	360.6793	362.7722
Fuel cost ($/h$)	41,651.6237	41,695.8717	41,686.7915	41,674.3363	41,693.9589
Power loss (MW)	15.33112	N/A	15.2403	15.0021	N/A

the proposed method, yields a gain of 22.7126 $/h. In this way, it earns $545.1024 per day and $198,962.376 per year. This result shows that the proposed method performs better computation and usability than the methods in the literature for the IEEE 57-bus test system. At the same time, the fuel cost curve of the proposed method in Figure 6 seems to converge faster and has a lower fuel cost than the standard GSA and TLBO algorithms.

3.2. Turkey's 22-bus power system and the results obtained

Turkey's 22-bus power system is a power system including 22 active buses, 8 generators, 14 load buses, and 26 transmissions lines [26]. In this power system, the base power is taken as 100 MVA and the active power demand is 4000 MW. Power constraints, cost coefficients, and the single-line diagram of Turkey's 22-bus power system are given in Appendixes A and B [26]. For this power system, the base power is taken as 100 MVA and the active power demand is 4000 MW, and the data were taken from [26].

After testing the success of the proposed method for the EDP solution of the IEEE 30- and 57-bus standard test systems, Turkey's 22-bus power system was implemented for minimum fuel cost calculation.

Table 7. Statistical comparison of simulation results of the IEEE 57-bus test system with other studies.

Methods	Fuel cost ($/h)			SD	Run time(s)
	Best	Mean	Worst		
The proposed method	41,651.6237	41,662.0328	41,694.3861	1.52	12.058
GSA	41,693.4532	42,125.6891	43,684.5248	50.14	15.216
GSA [14]	41,695.8717	N/A	N/A	N/A	N/A
TLBO	41,685.2434	41,755.2244	41,874.9662	15.11	17.851
TLBO[18]	41,686.7915	N/A	N/A	N/A	N/A
TLBO [19]	41,688.8512	41,693.1552	41,698.0085	12.72	N/A
PSO [19]	41,695.1483	41,714.1392	41,717.5173	12.99	N/A
CMICA4 [19]	41,674.3363	41,676.4205	41,678.2119	1.96	N/A
EADDE [20]	41,713.62	N/A	N/A	N/A	N/A
FHSA [21]	42,018.88	N/A	N/A	N/A	N/A
ABC [12]	41,693.9589	N/A	N/A	N/A	N/A
MICA-TLA [18]	41,675.0545	N/A	N/A	N/A	N/A

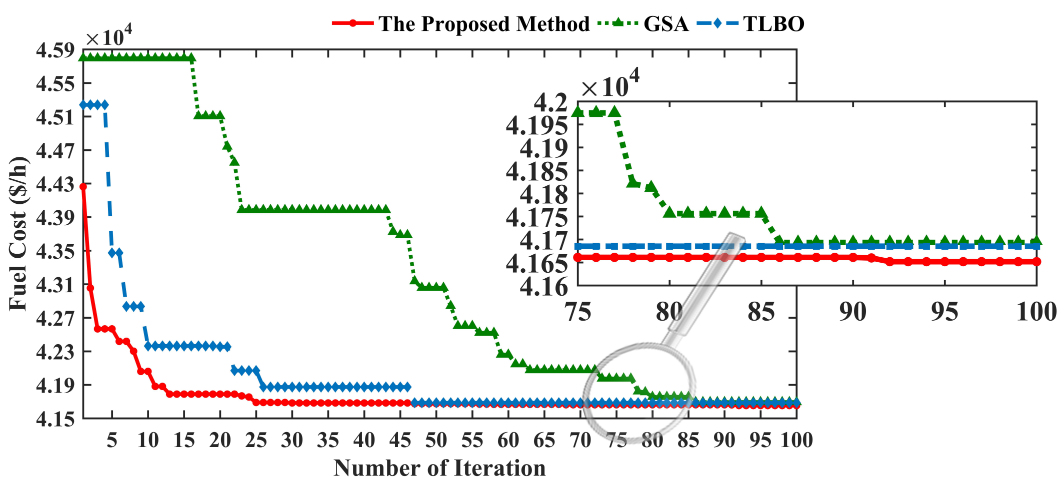

Figure 6. Variation of the fuel cost convergence performance of the proposed method with the number of iterations in the IEEE 57-bus system.

At the same time, the standard GSA and TLBO methods, as well as the proposed method, were applied to compare the calculation of the minimum fuel cost in Turkey's 22-bus power system. For experimental studies, these algorithms were tested in 30 independent runs. The active power, minimum fuel cost, and lost power values are shown in Table 8 as a comparison.

With the proposed method, the fuel cost of Turkey's 22-bus power system was found to be a minimum of 81,170.235 $/h, average of 81,247.498 $/h, and maximum of 82,042.936 $/h, and these statistical results are compared with other methods in Table 9. A gain of 83.755 $/h was obtained from the standard TLBO method closest to the minimum fuel cost found by the proposed method. As long as the demanded power does not change, the proposed method earns $2010.12 per day and $733,693.8 per year. It can be seen from Table 9 that the proposed method calculates better fuel cost and time than other standard algorithms. At the same time,

Table 8. Comparison of power values and minimum fuel cost in Turkey's 22-bus power system between the proposed and other methods.

Variables	The proposed method	GSA	TLBO	ABC [13]	Newton-based [28]
P_1 (MW)	395.7683	572.7422	377.7344	354.091	456.609
P_{16} (MW)	506.0358	428.6422	501.8855	549.567	569.120
P_{17} (MW)	660.0945	601.1859	635.6059	659.277	584.335
P_{18} (MW)	555.8217	506.2401	600	578.028	573.390
P_{19} (MW)	391.4171	426.8746	408.7455	401.343	378.541
P_{20} (MW)	390.2175	339.7697	369.6662	377.125	417.253
P_{21} (MW)	566.4899	605.9818	589.5085	575.712	564.935
P_{22} (MW)	564.3831	561.8255	552.9533	534.259	574.162
Fuel cost ($\$/h$)	81,170.235	82,288.84	81,253.99	81,421	83,258
Power loss (MW)	30.2279	43.262	36.0993	30.076	118.318

the proposed method in Figure 7 seems to converge faster than the other algorithms for the fuel cost curve and has a lower fuel cost.

Table 9. Statistical comparison of simulation results of Turkey's 22-bus power system with other studies and standard algorithms.

Methods	Fuel cost ($/h)			SD	Run time (s)
	Best	Mean	Worst		
The proposed method	81,170.235	81,247.498	82,042.936	5.62	12.42
GSA	82,288.843	83,385.713	83,818.414	32.14	14.28
TLBO	81,253.99	81,382.255	81,986.811	15.91	16.03
ABC [13]	81,421	N/A	N/A	N/A	N/A
Newton-based [28]	83,258	N/A	N/A	N/A	N/A

4. Conclusions

In this study, the GSA-TLBO method, which is a hybrid of the standard GSA algorithm in the global search space and TLBO in the local search space, has been proposed. The proposed method is then applied to the solution of the G01 benchmark problem, which is a constrained optimization problem. The standard GSA and TLBO were compared statistically. It was seen that the proposed method has found the solution of the G01 problem better than other standard algorithms. The proposed method was then applied to the IEEE 30- and 57-bus test systems, which are frequently used in the literature to solve the EDPs of power systems. It was found that the proposed method minimizes the CPU run-time as well as fuel cost. After the IEEE 30-bus and 57-bus test systems, it was applied to Turkey's 22-bus power system and was compared with the results of other standard algorithms. It is seen that the proposed method minimizes the fuel cost in Turkey's 22-bus power system with less run-time than the other optimization techniques.

As a result of the comparison, it has been determined that the proposed method is a quicker, more effective, more reliable, and usable calculation method in the solution of EDPs. It can be seen that the proposed method can be used successfully with good quality and performance for EDP optimization. At the

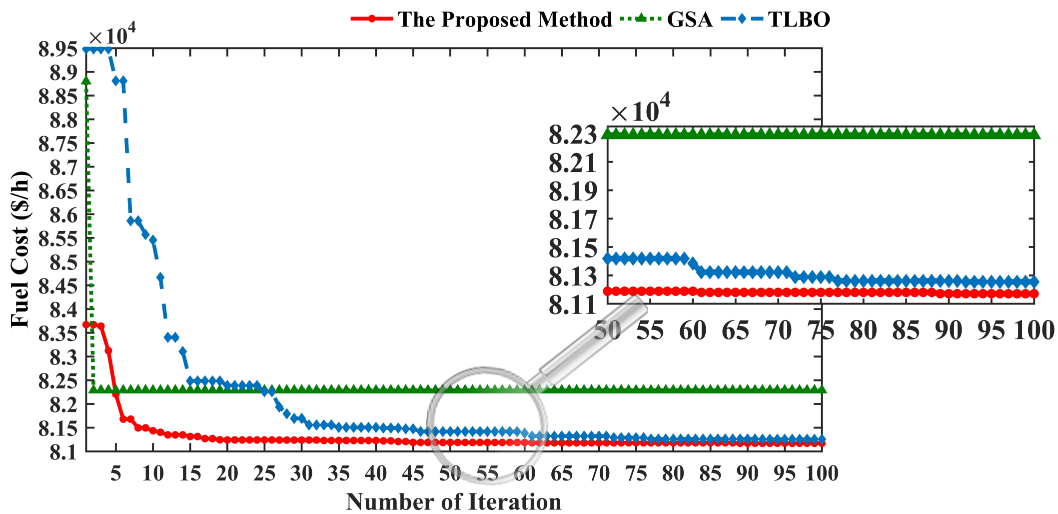

Figure 7. Variation of the fuel cost convergence performance of the proposed method with the number of iterations in Turkey's 22-bus power system.

same time, the new method used in this study can be used to solve other constrained optimization problems like large-scale power systems.

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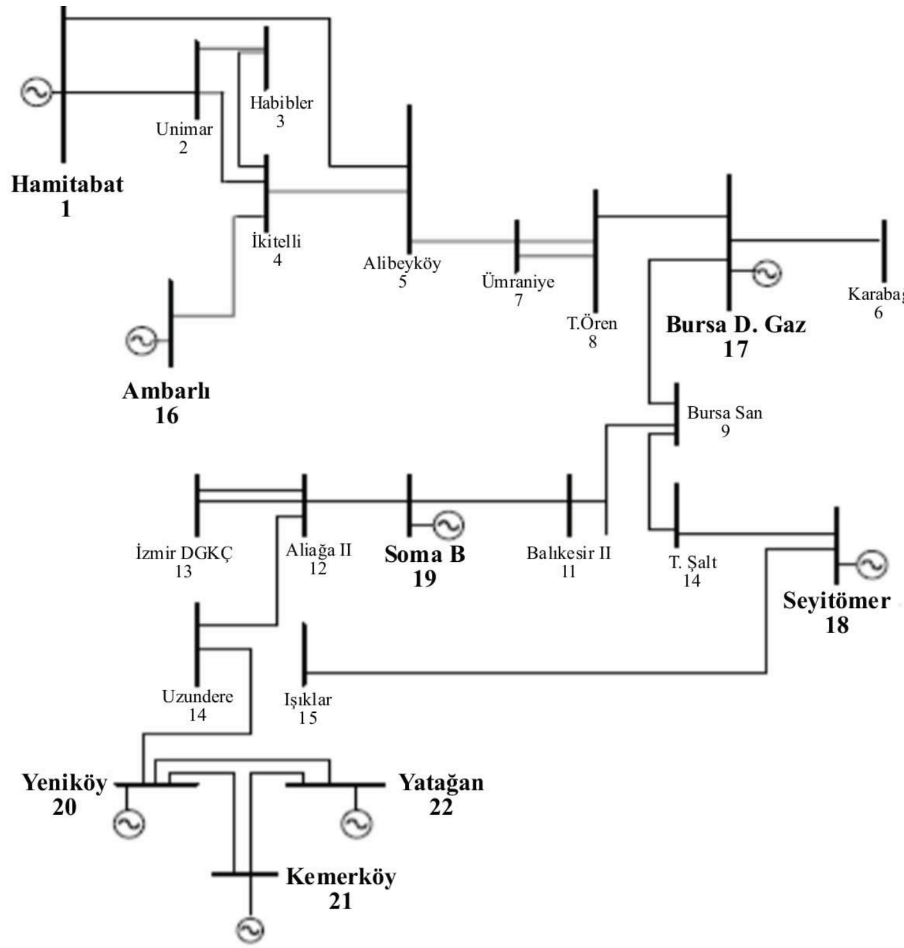
Appendix A. Single-line diagram of Turkey's 22-bus power system [26].



Appendix B. Power limit values and fuel cost coefficients of Turkey's 22-bus power system [26].

Bus no.	Power plant	Fuel type	P_i^{min} (MW)	P_i^{max}(MW)	a_i (\$/h)	b_i (\$/MWh)	c_i (\$/MW^{2}h)
P_1	Hamitabat	Natural gas	190	1120	6595.5	7.0663	0.0168
P_{16}	Ambarlı	Fuel oil	245	1350	7290.6	7.2592	0.1270
P_{17}	Bursa D.Gaz	Natural gas	318	1432	6780.5	5.6820	0.0106
P_{18}	Seyitömer	Coal	150	600	1564.4	3.1288	0.0139
P_{19}	Soma B	Coal	210	990	5134.1	6.2232	0.0168
P_{20}	Yeniköy	Coal	110	420	1159.5	3.3128	0.0210
P_{21}	Kemerköy	Coal	140	630	1697.0	3.2324	0.0137
P_{22}	Yatağan	Coal	140	630	1822.8	3.4720	0.0147