Turkish Journal of Electrical Engineering & Computer Sciences

http://journals.tubitak.gov.tr/elektrik/

Research Article

Turk J Elec Eng & Comp Sci
(2016) 24: 3769 – 3781

doi:10.3906/elk-1412-152

Gravitational search algorithm-based dynamic economic dispatch by estimating transmission system losses using A-loss coefficients

Ram Jethmalani CHINASAMY HEMPARUVA*, **Sishaj Pulikottil SIMON**, **Sundareswaran KINATTINGAL**, **Srinivasa Rao Nayak PANUGOTHU**
National Institute of Technology, Tiruchirappalli, India

Received: 23.12.2014 • **Accepted/Published Online:** 11.06.2015 • **Final Version:** 20.06.2016

Abstract: Dynamic economic dispatch (DED) is an important problem in power system generation, operation, planning, and control. The objective of the DED problem is to schedule power generation for the online units over a time horizon, satisfying the unit and ramp rate constraints. Here, valve point loading effects that cause nonsmoothness of the objective function is also considered while solving the DED. The accuracy of the solution not only depends on the optimal scheduling of generating units, but it also lies in accuracy while estimating transmission system losses. Generally, B-loss coefficients are used in estimating transmission losses. However, in the literature, A-loss coefficients are found to be at par with B-loss coefficients in estimating transmission system losses. Therefore, in this paper, the performance in estimating the transmission system losses using A-loss coefficients are investigated through the solution of the DED problem. Here, a recently evolved heuristic search technique called the gravitational search algorithm is used for solving the DED. The feasibility of the proposed method is tested and validated on standard benchmark test systems such as the IEEE 30-bus system, IEEE 39-bus system, and IEEE 118-bus system. All simulations are carried out using SCILAB 5.4 (www.scilab.org), which is open-source software.

Key words: A-loss coefficients, gravitational search algorithm, dynamic economic dispatch

1. Introduction

The economic dispatch (ED) problem involves the scheduling of optimal generation of committed units to minimize the total operating cost of the power system. Here, operating constraints such as power balance constraint and generator operating limit constraints are considered. However, to avoid shortening of equipment life, thermal gradients inside the turbine should be maintained within safe limits. This mechanical constraint is translated into limits on the rate of increase of the electrical output and is known as the ramp rate limit, which is vital in solving the dynamic economic dispatch (DED) problem [1]. Therefore, the DED is an extension of the conventional ED problem in which ramp rate limits of generating units are taken into account [2,3].

Traditionally, the cost function of the thermal power generating unit is assumed to be linear. However, the cost function of the generating unit is nonlinear, nonconvex, and nonsmooth due to multiple steam admission valves in the turbine [4]. Therefore, the conventional optimization techniques, which require convex characteristics, cannot be used to solve an optimization problem with nonconvex input-output characteristics [5].

In the literature, various heuristic optimization algorithms are proposed to solve the DED problem with

*Correspondence: malanisuryakumaran@gmail.com

a nonsmooth cost function [3,4,6–17]. Heuristic algorithms do not guarantee the global optima. However, a reasonable near optimal solution is always guaranteed [18]. Rashedi et al. developed a gravitational search algorithm (GSA) to solve nonlinear optimization problems [19]. Duman et al. [20] proposed the use of the GSA to solve the ED problem in which conventional B-loss coefficients are used to evaluate the transmission losses. Güvenç et al. proposed the use of the GSA to solve combined emission economic dispatch (CEED) [21]. Shah et al. proposed an opposition-based GSA to solve CEED [22]. Swain et al. proposed the use of GSA in solving the DED [23]. However, transmission network losses were not considered in their work. While solving the DED, it is vital to calculate the transmission network losses.

Transmission losses in a power system network are generally calculated using B-loss coefficients [24]. However, the losses calculated using B-loss coefficients need not be accurate [25]. In [26], Ziari et al. proposed polynomial loss coefficients to calculate transmission losses. Here, the transmission losses are expressed as second-order polynomial equations. These polynomial loss coefficients are obtained by using a curve-fitting technique, which is a tedious process when a large power system network is considered. Nanda et al. proposed the use of A-loss coefficients in evaluating transmission losses [25]. A-loss coefficients when compared with B-loss coefficients are extremely robust and need not be reevaluated even for wide changes in the loading pattern [25]. In [27], A-loss coefficients were used to calculate transmission losses in ED. However, the use of A-loss coefficients in solving DED is not yet explored.

In this paper, the DED problem with a nonsmooth cost function is solved using the GSA. Here, the calculation of transmission network losses is carried out using A-loss coefficients. The A-loss coefficients are calculated at the nominal load using the perturbation technique. The performance of the proposed method is validated using standard benchmark test systems, namely the IEEE 30-, IEEE 39-, and IEEE 118-bus systems.

This article is organized as follows. In Section 2, the problem formulation of the DED is explained. In Section 3, the procedure for estimation of nominal A-loss coefficients using the perturbation technique is presented. In Section 4, implementation of the proposed method to solve the DED problem using the GSA is explained. The results and discussions are presented in Section 5. Finally, conclusions are given in Section 6.

2. DED problem formulation

The objective of the DED problem is to schedule the optimal generation of committed units to minimize the cost of generation, subject to power balance constraint, generator operating limit constraints, and ramp rate limit constraints. The fuel cost of unit i at hour t is expressed as in Eq. (1).

$$f_i\left(P_{i,t}\right) = a_i + b_i P_{i,t} + c_i P_{i,t}^2 + \left|e_i \sin\left(f_i\left(P_{\min,i} - P_{i,t}\right)\right)\right| \tag{1}$$

Here, the cost function of the generating unit is nonsmooth. When the load on a thermal generator is increased, it consumes more fuel and the steam admission valves are sequentially opened to feed the additional fuel required. When a valve is opened, the throttling losses increase rapidly, which in turn forces the cost function to be nonsmooth [5]. The objective function of the DED problem is mathematically expressed as in Eq. (2).

$$\text{Minimize } F_T = \sum_{t=1}^{T} \sum_{i=1}^{ng} f_i\left(P_{i,t}\right) \tag{2}$$

Subject to:

1) Real power balance constraint.

$$\sum_{i=1}^{ng} P_{i,t} = P_{Dt} + P_{Lt} \tag{3}$$

2) Generating unit operating limits constraint.

$$P_{\min,i} \leq P_i \leq P_{\max,i} for i = 1, 2, ...ng \tag{4}$$

3) Generating unit ramp rate limit constraints.

$$P_{\min,i,t} = \max \{P_{\min,i}, P_{i,t-1} - Ud_i\} \tag{5}$$

$$P_{\max,i,t} = \min \{P_{\max,i}, P_{i,t-1} + Up_i\} \tag{6}$$

Conventionally, transmission losses in a power system network are evaluated using B-loss coefficients as in Eq. (7). In the proposed work, transmission losses are calculated using A-loss coefficients as in Eq. (8).

$$P_L = \sum_{i=1}^{ng} \sum_{j=1}^{ng} P_i B_{ij} P_j + \sum_{j=1}^{ng} P_i B_{i0} + B_{00} \tag{7}$$

$$P_L = \left[\sum_{i=1}^{ng} A_i P_i\right]^2 \tag{8}$$

3. Evaluation of A-loss coefficients

A-loss coefficients are evaluated using the perturbation technique [25]. The step-by-step procedure to estimate A-loss coefficients is as follows.

1. Set generator number $i = 1$ and obtain the power flow solution for the base case. From the power flow solution, note the power generated by all the generators $(P_1^0, P_2^0 P_3^0 \ldots ..P_{ng}^0)$ and the real power losses (P_L^0). The superscript 0 represents that the solution is obtained at the base case.

2. If generator i is not the slack generator (r), then apply perturbation at generator i and obtain the power flow solution. From the power flow solution, note $[P_1^i, P_2^i P_3^i \ldots ..P_{ng}^i P_L^i]$. The superscript i represents that the solution is obtained by applying perturbation at generator i. For instance, consider a system with three generators and the powers generated by the generators in the base case are [50 MW 40 MW 60 MW]. If a perturbation of +5 MW is applied at the second generator bus, then the powers generated by the generators are [50 MW 45 MW 60 MW].

3. If $i = ng$, go to step 4. Else increment generator number $i = i + 1$ and go to step 2.

4. Solve Eq. (9) and obtain A-loss coefficients.

$$\begin{bmatrix} \sqrt{P_L^0} \\ . \\ \sqrt{P_L^i} \\ . \\ \sqrt{P_L^{ng}} \end{bmatrix} = \begin{bmatrix} P_1^0 & P_i^0 & P_{ng}^0 \\ . & . & . \\ (P_1^i) & (P_i^i) & P_{ng}^2 \\ . & . & . \\ (P_1^{ng}) & P_i^{ng} & (P_{ng}^{ng}) \end{bmatrix} \begin{bmatrix} A_1 \\ . \\ A_i \\ . \\ A_{ng} \end{bmatrix} \qquad i = 1...ng, \quad i \neq r \tag{9}$$

4. Implementation of GSA for DED using A-loss coefficients

The GSA is a heuristic algorithm developed by simulating the laws of gravitation and motion. This algorithm was developed by Rashedi et al. [19].It is a population search-based algorithm used to solve nonlinear and nonconvex optimization problems. Here, the probable solutions are represented as the position of objects in the universe.

Each object in the universe attracts every other object with a gravitational force. The gravitational force between two objects is directly proportional to their masses and inversely proportional to the square of the distance between them. As a result of the gravitational pull exerted on one object by the other object, it moves. If more objects are present, then the movement of each object is governed by its mass and the vector sum of the gravitational pull exerted on it by all other objects. These principles of gravitation and motion are incorporated into the GSA.

In the proposed method, the DED is solved using the GSA, in which transmission losses are evaluated by using A-loss coefficients. The step-by-step procedure in implementing the GSA to solve the DED is as follows:

1. Read system data, load profile, tolerance in power balance mismatch (PBM), number of objects (N), lifespan of the universe (Γ_{max}), percentage of objects that can attract other objects at the end of the universe (FP), and initial gravitational constant (G_0).

2. Evaluate A-loss coefficients at the nominal load and initialize $t = 1$.

3. Initialize age of the universe (Γ) as 1, acceleration (a) and velocity (V) of each object in universe as 0, and population of N objects randomly. Each object is represented by its position in the ng dimensional space as a vector, $X_I = [P_I^1, P_I^2, \ldots P_I^i, \ldots, P_I^{ng}]'$. Each element in the vector X_I represents the real power generated by each generator. Then the entire population can be expressed as in Eq. (10). Here, the objects are generated in such a way that they satisfy generator operating limit constraints. The position of object I in dimension i is calculated as in Eq. (11).

$$X = \begin{bmatrix} P_1^1 & P_2^1 & \cdots & P_I^1 & \cdots & P_N^1 \\ . & . & \cdots & . & \cdots & . \\ P_1^i & P_2^i & \cdots & P_I^i & \cdots & p_N^i \\ . & . & \cdots & . & \cdots & . \\ P_1^{ng} & P_2^{ng} & \cdots & P_I^{ng} & \cdots & p_N^{ng} \end{bmatrix} \tag{10}$$

$$P_I^i = rand * (P_{i,max} - P_{i,min}) + P_{i,min} \tag{11}$$

4. Calculate the fitness of each object in the universe as in Eq. (12).

$$fit(X_I) = \sum\nolimits_{i=1}^{ng} f_i\left(P_{i,t}\right) \tag{12}$$

5. Calculate the mass of each object in the current population by using Eq. (13).

$$M_I\left(\Gamma\right) = \frac{m_I\left(\Gamma\right)}{\sum\limits_{J=1}^{N} m_I\left(\Gamma\right)} \tag{13}$$

Here, $m_I(\Gamma)$is expressed as in Eq. (14).

$$m_I(\Gamma) = \frac{fit_I(\Gamma) - worst(\Gamma)}{best(\Gamma) - worst(\Gamma)} \tag{14}$$

Here, 'best' and 'worst' are the minimum and maximum fitness values, respectively.

6. Calculate the gravitational force acting on object I in dimension i by using Eq. (15).

$$Fg_I^i(\Gamma) = rand_J \sum_{J=1, J \in kbest, J \neq I}^{N} Fg_{IJ}^i(\Gamma) \tag{15}$$

Here, $rand$ is a random variable, $Fg_{IJ}^i is$the force exerted on object I by object J, and $kbest$ is the number of objects in the current population that can attract another object.

$$kbest = FP + \left(1 - \frac{\Gamma}{\Gamma_{max}}\right) * (100 - FP) \tag{16}$$

$$Fg_{IJ}^i(\Gamma) = G(\Gamma) \frac{M_I M_J}{R_{IJ} + \xi} \left(P_J^i(\Gamma) - P_I^i(\Gamma)\right) \tag{17}$$

Here, R_{IJ} is the distance between objects I and J, ξ is a small numeric constant, and $G(\Gamma)$ is the gravitational constant at the current age of the universe, which is expressed as in Eq. (18).

$$G(\Gamma) = G_0 e^{-\alpha\left[\frac{\Gamma}{\Gamma_{max}}\right]} \tag{18}$$

Here, α is a constant.

7. Calculate the acceleration of each object in the current population by using Eq. (19).

$$a_I(\Gamma) = \frac{Fg_I(\Gamma)}{M_I(\Gamma)} \tag{19}$$

8. Update the velocity and position of each object by using Eq. (20) and Eq. (21), respectively.

$$v_I^d(\Gamma + 1) = rand_J * v_I^d(\Gamma) + a_I^d(\Gamma) \tag{20}$$

$$X_I^d(\Gamma + 1) = X_I^d(\Gamma) + v_I^d(\Gamma + 1) \tag{21}$$

Update the best fitness value obtained until the current age of the universe (Γ) as the optimum cost for the current time interval(t).

9. If $\Gamma = \Gamma_{max}$, then proceed to the next step. Otherwise, increment Γ and go to step 5.

10. If $t = T$, then stop the iterations. Otherwise, increment t, update the operating limits using Eqs. (5) and (6), and go to step 3.

4.1. Repair strategy for constraint management

When an initial solution is randomly generated or if the object position is modified, violation of the power balance constraint of Eq. (3) and ramp rate constraints should be checked (Eqs. (5) and (6)). [28]. The PBM is the difference between the sum of power generated by all generators and the sum of load demand and transmission loss. If the power balance constraint is violated (PBM >Tol), then the power generated by each generating unit is modified to make the PBM less than the specified tolerance. Here, the PBM is equally shared between all the generating units. For example, let = 3, object = [47 50 60], and power demand = 150 MW, and losses corresponding to the object = 1 MW. Then the PBM will be equal to 6 MW. Therefore, the position of the object is varied as = [45 48 58]. If generator operating limit constraints are violated, then the generator that violates the limit will be brought back to its corresponding limit. For example, if the minimum limit on the first generator is 46 MW, then the position of object is modified as [46 48 58]. Here, modification of generating unit output carried out to satisfy one constraint leads to violation of another constraint. In order to satisfy all the constraints of Eqs. (3), (5), and (6) simultaneously, the above corrections are repeated for a preset number of iterations. Here, the generating unit that undergoes correction for operating limit constraints is restrained from further PBM sharing. Once the repair strategy is completed, the objects that violate the constraints will be penalized during evaluation.

5. Results and discussions

All simulations are carried out using SCILAB 5.4 and executed on a personal computer with 4 GB RAM and 2.4 GHz processor. The proposed method of solving the DED problem using the GSA with A-loss coefficients is validated on three different test systems after careful parameter selection. The DED is solved using the GSA with A-loss coefficients. It should be noted that the loss coefficients are calculated at the nominal load of the test system. The tolerance value for the PBM is taken as 10^{-8} per unit.

5.1. GSA parameter selection

Prior to validation of the proposed method, the parameters of the GSA, such as the number of objects (N), the age of the universe (Γ_{max}), and the final percentage (FP) are selected. For each parameter, several values are taken between the boundaries. Here, $N\epsilon 10, 20, \ldots, 300\}$, $\Gamma_{\max}\epsilon 10, 20, \ldots, 50\}$, and $FP\epsilon 2, 4, \ldots, 32\}$. For each combination of parameters the DED is solved for five trials using the GSA to get statistical information about the average evolution. The optimum combinations of parameters for each test system are given in Table 1.

Table 1. GSA parameters.

IEEE system	Number of objects	Final percentage (%)	Lifespan of universe
30-bus	100	8	40
39-bus	300	4	30
118-bus	300	2	30

5.2. Test case 1: IEEE 30-bus system

The data for the IEEE 30-bus system are adapted from [24,29,30]. The valve point coefficients of the generators are given in Table 2. The nominal loss coefficients of the system are given in Table 3. Owing to the randomness of the heuristic algorithms, their performance cannot be judged by the result of a single run. Many trials should be carried out to acquire a useful conclusion about the performance of the algorithm [31]. Therefore, in Table

4, the DED results obtained using the GSA with A-loss coefficients and the GSA with B-loss coefficients are compared in terms of best, worst, and average total fuel cost obtained over 10 trials. The generation schedules of units obtained using the GSA with A-loss coefficients are given in Table 5. In Table 6, the total fuel cost obtained using the proposed method is compared with total fuel cost obtained using various other methods.

Table 2. IEEE 30-bus system: valve point coefficients.

Gen. no.	1	2	3	4	5	6
e ($)	0	0	40	30	0	0
f (MW^{-1})	0	0	0.08	0.09	0	0

Table 3. IEEE 30-bus system: nominal loss coefficients.

A	B						B0	B00
0.01424	0.00022	0.00011	–0.00001	–0.00001	0.00001	0.00004	–0.00003	0.14071
0.00883	0.00011	0.00016	0.00000	–0.00001	0.00000	0.00003	0.00154	
–0.00113	–0.00001	0.00000	0.00024	–0.00010	–0.00010	–0.00007	–0.00401	
0.00228	–0.00001	–0.00001	–0.00010	0.00019	0.00007	0.00004	0.00283	
0.00231	0.00001	0.00000	–0.00010	0.00007	0.00016	0.00000	0.00116	
0.00530	0.00004	0.00003	–0.00007	0.00004	0.00000	0.00026	0.00363	

Table 4. IEEE 30-bus system: GSA results with A- and B-loss coefficients.

Parameters	GSA with A-loss coefficients	GSA with B-loss coefficients
Best cost ($)	13,100.6	13,110.6
Worst cost ($)	13,102.7	13,110.8
Mean cost ($)	13,101.6	13,110.7

5.3. Test case 2: IEEE 39-bus system

The data for the IEEE 39-bus system are adapted from [10,32]. The loss coefficients are calculated at the nominal load and the same loss coefficients are used throughout the schedule. The nominal loss coefficients of the system are given in Table 7. The DED is solved using the GSA with A-loss coefficients for 10 trial runs and the generation schedule resulting in minimum fuel cost is given in Table 8. In Table 9, the proposed method is compared with the results of the GSA with B-loss coefficients in terms of best, worst, and average total fuel cost obtained over 10 trials. Table 10 gives the comparison of total fuel cost obtained using the proposed method with total fuel cost reported in the literature.

5.4. Test case 3: IEEE 118-bus system

The data for the IEEE 118-bus system are adapted from [29]. The DED is solved using the GSA with A-loss coefficients. The hourly load, generation, losses, and fuel cost of the obtained generation schedule are given in Table 11. The total fuel costs obtained by solving the DED using the proposed method and other methods available in literature are compared in Table 12.

Table 5. IEEE 30-bus system: generation schedule using the GSA with A-loss coefficients.

Load (MW)	P_1	P_2	P_3	P_4	P_5	P_6	P_L	Cost ($)
166	92.93	28.74	15.05	10.04	10.02	12.02	2.79	418.1
196	117.66	34.88	15	10	10.78	12	4.32	506.8
229	148.72	39.66	15	10	10.17	12	6.56	612.4
267	175.59	51.39	15	10	12.34	12	9.32	745.8
283.4	189.98	53.29	15	10	13.88	12	10.74	806.7
272	181.80	49.61	15	10	13.36	12	9.78	764.0
246	161.62	44.81	15	10	10.35	12	7.79	670.5
213	129.70	41.58	15	10.04	10	12	5.32	560.3
192	114.62	34.21	15	10	10	12.29	4.11	494.4
161	87.26	29.21	15	10	10	12.06	2.54	403.9
147	79.43	22.58	15	10.02	10	12.00	2.02	365.6
160	88.00	27.50	15	10.00	10	12.03	2.52	401.0
170	96.05	29.92	15	10.01	10	12	2.97	429.3
185	106.48	35.15	15	10	10	12.06	3.68	473.3
208	126.86	39.01	15	10	10.16	12	5.04	544.0
232	150.17	41.16	15	10	10.40	12	6.74	622.5
246	162.60	43.84	15	10	10.38	12	7.82	670.5
241	157.56	43.58	15	10	10.27	12	7.41	653.2
236	152.58	42.87	15.01	10	10	12.54	7.01	636.2
225	139.80	43.50	15	10	10.80	12.00	6.10	599.4
204	125.98	35.83	15.01	10.01	10.01	12.01	4.85	531.4
182	105.34	33.11	15	10	10.10	12	3.55	464.3
161	87.52	29.01	15	10	10	12.02	2.54	403.8
131	65.44	20.00	15	10	10	12	1.44	323.5
Total fuel cost								13,100.6

Table 6. IEEE 30-bus system: comparison of GSA result.

SI no.	Method	Total fuel cost ($)
1	Evolutionary programming (EP)	13,117
2	EP-sequential quadratic programming	13,112
3	Modified hybrid evolutionary programming	13,111
4	Genetic algorithm	13,135
5	Particle swarm optimization	13,155
6	Artificial bee colony algorithm	13,121
7	Artificial immune system	13,111
8	GSA with B-loss coefficients	13,111
9	GSA with A-loss coefficients	13,100

Table 7. IEEE 39-bus system: nominal loss coefficients.

A ($\times 10^{-5}$)									
88.1	118.9	211.2	200.5	168.7	190.5	246.6	298	44.4	83.8
B ($\times 10^{-5}$)									
1.9	1.5	–0.3	–0.2	–0.4	–0.4	–1.9	–3.2	0.6	0.1
1.5	2.4	–0.4	–0.2	–0.3	–0.3	–1.4	–2.4	0.3	0.2
–0.3	–0.4	4.4	1.8	0.8	0.8	–0.6	–0.9	–2.6	–0.9
–0.2	–0.2	1.8	3.2	0.4	0.4	–0.4	–0.5	–1	–0.4
–0.4	–0.3	0.8	0.4	2.5	2.2	–0.4	–0.6	–2.2	–0.6
–0.4	–0.3	0.8	0.4	2.2	3.4	–0.4	–0.6	–2.2	–0.7
–1.9	–1.4	–0.6	–0.4	–0.4	–0.4	15.4	7.4	–3.9	–0.1
–3.2	–2.4	–0.9	–0.5	–0.6	–0.6	7.4	24.8	–6.5	–1.8
0.6	0.3	–2.6	–1	–2.2	–2.2	–3.9	–6.5	12.3	2
0.1	0.2	–0.9	–0.4	–0.6	–0.7	–0.1	–1.8	2	7.6
B0 ($\times 10^{-5}$)									
774.1	493.4	742.1	–75.8	251.8	288.8	–2585	–4658	317.3	–841.8
B00 = 6.0343285									

Table 8. IEEE 39-bus system: generation schedule using the GSA with A-loss coefficients.

Load (MW)	P_1	P_2	P_3	P_4	P_5	P_6	P_7	P_8	P_9	P_{10}	$\sum P_i$	P_L	Cost ($)
1036	150.24	135.24	194.33	60.24	123.11	122.69	129.83	47.24	20.24	55	1038.16	2.15	28,326.5
1110	226.91	135.25	191.21	60.25	123.13	123.15	129.85	47.25	20.25	55	1112.25	2.25	29,921.9
1258	303.57	142.56	185.54	60.29	173.13	143.11	129.91	47.32	20.32	55	1260.78	2.78	33,453.9
1406	380.22	222.56	197.43	60.35	173.09	122.80	129.94	47.35	20.35	55	1409.07	3.07	36,416.3
1480	380.27	222.67	185.59	60.40	223.00	158.88	129.99	47.40	20.40	55	1483.61	3.61	38,127.0
1628	454.24	300.47	258.34	60.57	187.77	120.61	127.79	47.00	20.00	55	1631.79	3.79	41,882.9
1702	379.68	309.36	303.82	87.55	222.56	122.52	129.42	76.83	20.00	55	1706.76	4.76	43,296.0
1776	457.09	317.33	286.37	120.81	223.12	122.93	130.00	47.59	20.59	55	1780.86	4.86	44,740.2
1924	457.39	397.33	306.24	131.65	223.29	160.00	130.00	47.89	20.89	55	1929.70	5.70	48,115.6
2072	461.48	403.59	336.97	181.65	221.84	160.00	130.00	77.85	50.89	55	2079.27	7.27	52,160.7
2146	457.92	460.00	299.58	231.64	223.72	160.00	130.00	82.68	53.47	55	2154.01	8.01	53,943.2
2220	458.60	460.00	340.00	242.56	243.00	160.00	130.00	87.41	52.10	55	2228.69	8.69	55,951.7
2072	457.74	397.67	310.98	242.22	223.30	123.38	130.00	86.28	53.01	55	2079.59	7.59	51,686.0
1924	379.72	393.62	278.52	241.02	222.42	122.32	101.17	85.12	51.92	55	1930.82	6.82	48,762.6
1776	301.12	387.68	307.25	191.02	214.37	121.97	95.01	81.89	26.38	55	1781.70	5.70	45,681.8
1554	300.72	307.68	301.28	141.02	164.37	122.35	93.72	51.89	20.00	55	1558.04	4.04	40,380.0
1480	302.51	308.28	300.32	117.75	114.37	116.43	96.85	47.00	24.95	55	1483.45	3.45	38,625.0
1628	306.34	307.88	340.00	115.27	126.08	126.23	126.85	77.00	51.98	55	1632.64	4.64	42,190.1
1876	381.79	384.71	322.32	119.69	171.73	119.97	127.02	47.17	51.67	55	1781.06	5.06	45,175.5
2072	454.81	457.09	305.97	169.69	216.87	160.00	130.00	77.17	52.54	55	2079.14	7.14	52,446.5
1824	455.96	389.00	322.01	119.88	222.09	121.91	129.06	84.77	30.20	55	1929.87	5.87	48,375.1
1628	380.29	309.99	283.64	70.87	173.18	122.89	130.00	85.81	20.50	55	1632.20	4.20	41,443.2
1332	306.10	230.19	266.45	60.00	123.18	117.77	100.00	56.06	20.00	55	1334.76	2.76	35,680.0
1184	305.83	222.68	199.95	60.00	73.18	109.75	92.64	47.00	20.00	55	1186.03	2.04	31,983.0
Total fuel cost ($)													1,028,765

Table 9. IEEE 39-bus system: statistical results of the GSA with A- and B-loss coefficients.

Parameters	GSA with A-loss coefficients	GSA with B-loss coefficients
Best cost ($)	1,028,765	1,042,025
Worst cost ($)	1,040,894	1,058,345
Mean cost ($)	1,036,910	1,050,836

Table 10. IEEE 39-bus system: comparison of GSA results.

SI no.	Method	Total fuel cost ($)
1	Evolutionary programming (EP) [6]	1,054,685
2	EP-sequential quadratic programming [6]	1,052,668
3	Modified hybrid evolutionary programming [6]	1,050,054
4	Genetic algorithm [15]	1,052,251
5	Particle swarm optimization [15]	1,048,410
6	Artificial bee colony algorithm [15]	1,043,381
7	Artificial immune system [4]	1,045,715
8	GSA with B-loss coefficients	1,042,025
9	GSA with A-loss coefficients	1,028,765

From the above results, it is clear that the proposed GSA gives better results than other methods in the literature when A- as well as B-loss coefficients are used. The best, worst, and average costs obtained using the GSA with A-loss coefficients are less compared to the GSA with B-loss coefficients. Therefore, it is apparent that the fuel cost reduces when A-loss coefficients replace conventional B-loss coefficients. Hence, the proposed GSA with A-loss coefficients is a competent method for solving the DED problem. When the A-loss coefficients are used to evaluate transmission losses in a DED problem, the optimum fuel cost is reduced. The fuel cost is reduced as the use of A-loss coefficients gives more accurate losses, which in turn shifts the dispatch from one operating point to the other due to the dynamic nature of the power system network.

Table 11. IEEE 118-bus system: generation schedule using the GSA with A-loss coefficients.

Hour	Load (MW)	$\sum P_i$ (MW)	P_L (MW)	Cost ($)	Hour	Load (MW)	$\sum P_i$ (MW)	P_L (MW)	Cost ($)
1	4298	4337.79	39.79	161,993.3	13	4400	4441.11	41.11	165,995
2	5074	5144.60	70.60	195,088.3	14	4788	4856.14	68.14	181,855
3	5928	6008.69	80.69	233,331.8	15	5384	5473.93	89.93	208,496
4	6912	7056.45	144.45	289,061.4	16	6006	6103.41	97.41	237,753
5	7336	7546.82	210.82	414,905.7	17	6368	6471.11	103.11	258,105
6	7040	7246.40	206.40	310,018.0	18	6238	6335.21	97.21	249,353
7	6368	6526.94	158.94	260,220.5	19	6110	6221.68	111.68	243,797
8	5514	5609.87	95.87	215,196.0	20	5824	5924.09	100.09	230,426
9	4970	5027.99	57.99	190,496.0	21	5280	5364.38	84.38	203,724
10	4168	4226.97	58.97	156,834.2	22	4712	4751.85	39.85	178,395
11	3806	3838.46	32.46	144,182.3	23	4168	4210.44	42.44	156,660
12	4142	4182.16	40.16	156,504.5	24	3392	3431.19	39.19	128,762

Table 12. IEEE 118-bus system: comparison of GSA results.

SI no.	Method	Total fuel cost ($)
1	Evolutionary programming (EP)	5,951,021
2	EP-sequential quadratic programming	5,794,549
3	Modified hybrid evolutionary programming	5,753,894
4	Genetic algorithm	5,733,318
5	Particle swarm optimization	5,800,886
6	Artificial bee colony algorithm	5,912,620
7	Artificial immune system	5,609,163
8	GSA with B-loss coefficients	5,576,667
9	GSA with A-loss coefficients	5,171,157

6. Conclusion

This paper has employed A-loss coefficients in transmission loss evaluation while solving the DED. Here, the GSA is used to solve the DED. The feasibility of the proposed approach is demonstrated using various standard benchmark test systems. The comparison of the results of the proposed approach with the DED using the GSA with B-loss coefficients reveals that the total fuel cost reduces when A-loss coefficients are used. Therefore, the use of A-loss coefficients is found to be a better alternative for B-loss coefficients in transmission loss evaluation. Furthermore, the comparison of the results with other methods reported in the literature substantiates that the proposed method is very competent to solve the DED problem. The proposed method is applicable to small as well as large-scale power systems.

Nomenclature

a_i, b_i, c_i	Cost coefficients of generating unit i.
A_i	A-loss coefficients.
$B_{ij} B_{i0} B_{00}$	B-loss coefficients.
$Best$	Minimum fitness of objects in the current age.
c	Trial number for repair mechanism.
C	Maximum number of trials in repair strategy.
e_i, f_i	Valve point coefficients of generating unit i.
$E(i)$	Availability of generating unit i for repair.
$f_i\left(P_{i,t}\right)$	Fuel price of generating unit i at hour t.
fit	Fitness of objects.
Fg	Gravitational force.
FP	Final percentage
G	Gravitational constant.
$kbest$	Number of objects in the universe that can attract other objects.
M	Mass of objects.
ng	Number of generating units.
ngr	Number of generating units available for repair.
N	Number of objects in the universe.
P_{Dt}	Power demand at hour t.
$P_{i,t}$	Power generated by generating unit i at hour t.
P_{Lt}	Power loss at hour t.
$P_{\max,i}$	Maximum power that can be generated by generating unit i.
$P_{\min,i}$	Minimum power that can be generated by generating unit i.
PBM	Power balance mismatch.
r	Slack generator.
t	Load interval.
T	Number of time intervals.
Tol	Tolerance in power balance mismatch.
Ud_i	Ramp down limit of generating unit i.
Up_i	Ramp up limit of generating unit i.
V	Velocity of objects.
$Worst$	Maximum fitness of objects in the current age.
X	Initial solution.
a	Acceleration of objects.
Γ	Age of universe.
$\Gamma_{\max}$	Lifespan of universe.
v	Violation flag.

References

[1] Chandram K, Subrahmanyam N, Sydulu M. Brent method for dynamic economic dispatch with transmission losses. In: IEEE 2008 Power Engineering Society Transmission Distribution Conference and Exposition; 21–24 April 2008; Chicago, IL, USA. pp. 1-5.

[2] Han XS, Gooi HB, Kirschen DS. Dynamic economic dispatch: Feasible and optimal solutions. IEEE T Power Syst 2001; 16: 22-28.

[3] Manoharan PS, Kannan P, Baskar S, Irudhayarajan MW, Dhananjeyan V. Covariance matrix adapted evolution strategy algorithm- based solution to dynamic economic dispatch problems. Eng Optimiz 2009; 41: 635-657.

[4] Hemamalini S, Simon SP. Dynamic economic dispatch using artificial immune system for units with valve-point effect. Int J Elec Power 2011; 33: 868-874.

[5] Wood AJ, Wollenberg BF. Power Generation Operation and Control. 2nd ed. New York, NY, USA: Wiley, 1996.

[6] Victoire TAA, Jeyakumar AE. A modified hybrid EP–SQP approach for dynamic economic dispatch with valve-point effect. Int J Elec Power 2007; 27: 594-601.

[7] Sinha N, Chakrabarti R, Chattopadhyay PK. Evolutionary programming techniques for economic load dispatch. IEEE T Evolut Comput 2003; 7: 83-94.

[8] Pereira-Neto A, Unsihuay C, Saavedra OR. Efficient evolutionary strategy optimization procedure to solve the nonconvex economic dispatch problem with generator constraints. IEE P-Gener Transm D 2005; 152: 653-660.

[9] Wang Y, Zhou J, Qiu H, Lu Y. Improved chaotic particle swarm optimization algorithm for dynamic economic dispatch problem with valve-point effects. Energ Convers Manage 2010; 51: 2893-2900.

[10] Attaviriyanupap P, Kita H, Tanaka E, Hasegawa J. A hybrid EP and SQP for dynamic economic dispatch with nonsmooth fuel cost function. IEEE T Power Syst 2002; 17: 411-416.

[11] Lee JC, Lin WM, Liao GC, Tsao TP. Quantum genetic algorithm for dynamic economic dispatch with valve-point effects and including wind power system. Int J Elec Power 2011; 33: 189-197.

[12] Ongsakul W, Rungpayoonsak N. Constrained dynamic economic dispatch by simulated annealing/genetic algorithm. In: IEEE 2001 Power Industry Computer Applications Conference; 20–24 May 2001; Sydney, Australia. pp. 207-212.

[13] Panigrahi CK, Chattopadhyay PK, Chakrabarti RN, Basu M. Simulated annealing technique for dynamic economic dispatch. Electr Pow Compo Sys 2006; 34: 577-586.

[14] Basu M. Artificial immune system for dynamic economic dispatch. Int J Elec Power 2011; 33: 131-136.

[15] Hemamalini S, Simon SP. Dynamic economic dispatch using artificial bee colony algorithm for units with valve-point effect. Eur T Electr Power 2011; 21: 70-81.

[16] Mohammadi-Ivatloo B, Rabiee A, Soroudi A, Ehsan M. Imperialist competition algorithm for solving non-convex dynamic economic power dispatch. Energy 2012; 44: 228-240.

[17] Balamurugan R, Subramanian S. Differential evolution-based dynamic economic dispatch of generating units with valve-point effects. Electr Pow Compo Sys 2008; 36: 828-843.

[18] He D, Dong G, Wang F, Mao Z. Optimization of dynamic economic dispatch with valve-point effect using chaotic sequence based differential evolution algorithms. Energ Convers Manage 2011; 52: 1026-1032.

[19] Rashedi E, Nezamabadi-pour H, Saryazdi S. GSA: a gravitational search algorithm. Inform Sciences 2009; 179: 2232-2248.

[20] Duman S, Güvenç U, Yörükeren N. Gravitational search algorithm for economic dispatch with valve-point effects. Int Rev Electr Eng-I 2010; 5: 2890-2895.

[21] Güvenç U, Sönmez Y, Duman S, Yörükeren N. Combined economic and emission dispatch solution using gravitational search algorithm. Sci Iran 2012; 19: 1754-1762.

[22] Shaw B, Mukherjee V, Ghoshal SP. A novel opposition-based gravitational search algorithm for combined economic and emission dispatch problems of power systems. Int J Elec Power 2012; 35: 21-33.

[23] Swain RK, Meher KC, Mishra UC. Dynamic economic dispatch using hybrid gravitational search algorithm. In: IEEE 2012 Power, Control and Embedded Systems Conference; 17–19 December 2012; Allahabad, India. pp. 1-6.

[24] Saadat H. Power System Analysis. 1st ed. New York, NY, USA: McGraw-Hill, 1999.

[25] Nanda J, Lai LL, Ma JT, Rajkumar N, Nanda A, Prasad M. A novel approach to computationally efficient algorithms for transmission loss and line flow formulations. Int J Elec Power 1999; 21: 555-560.

[26] Ziari I, Jadid S, Jalilian A. A new method for modelling loss in a distribution network. In: IEEE 2006 Universities Power Engineering Conference; 6–8 September 2006; Newcastle, UK. pp. 393-397.

[27] Nanda J, Narayanan RB. Application of genetic algorithm to economic load dispatch with line flow constraint. Int J Elec Power 2002; 24: 723-729.

[28] Chandrasekaran K, Simon SP. Fuzzified artificial bee colony algorithm for nonsmooth and nonconvex multiobjective economic dispatch problem. Turk J Electr Eng Co 2013; 21: 1995-2014.

[29] Shahidehpour M, Wang Y. Communication and Control in Electric Power Systems: Applications of Parallel and Distributed Processing. 1st ed. Hoboken, NJ, USA: John Wiley and Sons, 2004.

[30] Simon SP, Padhy NP, Anand RS. An ant colony system approach for unit commitment problem. Int J Elec Power 2006; 28: 315-323.

[31] Manoharan PS, Kannan PS, Ramanathan V. A novel EP approach for multi-area economic dispatch with multiple fuel options. Turk J Electr Eng Co 2009; 17: 1-19.

[32] Athay T, Podmore R, Virmani S. A practical method for the direct analysis of transient stability. IEEE T Power Ap Syst 1979; 2: 573-584.