Annals of Electrical and Electronic Engineering, 1(3) 2018, Pages: 6-10

Published by IASE

Annals of Electrical and Electronic Engineering

Journal homepage: www.aeeej.org

On the non-convex economic power dispatch problem using artificial bee colony

T. H. Baba [1], Y. Itamoto [1, *], R. Lima [2]

[1]Department of Electrical Engineering, Doshisha University, Kyoto 610-0321, Japan
[2]Institute of Energy and Environment, University of São Paulo, São Paulo, Brazil

ARTICLE INFO

Article history:
Received 12 November 2017
Received in revised form
28 January 2018
Accepted 5 February 2018

Keywords:
Economic power dispatch
Artificial bee colony
Valve-point loading effects
Prohibited operating zones

ABSTRACT

A modified version of the artificial bee colony (ABC) algorithm is presented in this study by including a local search technique for solving the non-convex economic power dispatch problem. Total system losses, valve-point loading effects and prohibited operating zones have been incorporated in the problem formulation. The proposed technique is validated using an IEEE benchmark system with ten thermal units. Simulation results demonstrate that the proposed optimization algorithm has better convergence characteristics in comparison with the original ABC algorithm.

1. Introduction

The optimal power generation of thermal units with minimum production cost has become necessary due to the excessive increase of fuel prices. To satisfy this requirement, several research works have been proposed to solve the economic dispatch (ED). Various studies have considered the traditional ED problem where the production cost function of each thermal unit is approximated by a quadratic function (Chen and Wang, 1993; Wood and Wollenberg, 2012). Unfortunately, modern systems are with units that have prohibited operating zones (POZ) due to physical operation limitations. In addition, practical ED problem includes the valve-point loading effects in the cost function. These additional constraints make the problem with high nonlinear and discontinuous objective function. Thus, traditional optimization techniques proposed in the literature, such as Newton methods (Lin et al., 1992), lambda iteration (Park et al., 2005) and linear programming (Gar et al., 2001) cannot provide the best solution.

In recent years, several intelligent optimization techniques, such as genetic algorithms (GA), particle swarm optimization (PSO), bacterial foraging, artificial bee colony (ABC) and simulated annealing have been used to solve this non-convex and discontinuous ED problem (Yang et al., 2014; Jain et al., 2012; Bakirtzis et al., 1994).

Despite these metaheuristic methods have shown their ability to converge into reasonable solutions, they do not always guarantee the global optimal solutions. To overcome this drawback, numerous modified algorithms have been appeared. A combination of GA and micro-GA to improve global and local solution of ED problem is proposed in (Kherfane et al., 2014). An elitist real-coded GA based on non-uniform arithmetic crossover and mutation has been used to optimally schedule the generation of all generators of the IEEE 25-bus system (Bouzeboudja et al., 2005). A hybrid differential evolution and sequential quadratic programming for solving the power dispatch problem is suggested in (Elaiw et al., 2013). In the variable neighborhood search method is incorporated in the differential evolution algorithm in order to improve the optimal solution (Jasper and Aruldoss, 2013). Other modified and hybrid techniques that combine different metaheuristic algorithms have been presented in the two past decades to solve various form of the ED problem, such as combined hybrid differential PSO algorithm (Ramesh et al., 2010), PSO with Time Varying Operators (Jadoun et al., 2014), hybrid PSO and gravitational search algorithm (Jianga et al., 2014) and hybrid ant colony optimization-artificial bee colony-harmonic search algorithm (Sen and Mathur, 2016).

Recently, a new swarm based stochastic search algorithm called artificial bee colony that imitates the foraging behavior of bee colony (Karaboga, 2005; Labbi et al., 2014) is considered as efficient technique for complex optimization problem. However, the ABC algorithm has been criticized to its poor convergence rate and premature convergence due to the unbalanced exploration-exploitation processes. To overcome this disadvantage, a new modified ABC algorithm is proposed in this paper for the ED problem. This modified algorithm incorporates a local search technique at the end of each iteration to facilitate the convergence into the global optimum. Valve-point loading effects and POZ constraints have been included in the problem. The validation of the proposed optimization method has been evaluated on the well-known benchmark system with ten units.

2. ED problem formulation

The ED problem is considered as an optimization problem that aims to schedule the outputs of the thermal units so as to minimize the total fuel cost subject to the system the operating constraints, such as generation capacity, power balance, POZ and security constraints.

2.1. Total fuel cost function

Let consider a power system with N units. The total fuel cost in \$/h including valve-point loading effects can be expressed by the following equation (Tlijani et al., 2017).

[*] *Corresponding Author.*
Email Address: YItamoto@gmx.us (Y. Itamoto)
https://doi.org/10.21833/AEEE.2018.03.002

$$C_T = \sum_{i=1}^{N}\left[a_i + b_iP_i + c_i(P_i)^2 + \left|d_i \sin\{e_i(P_i^{min} - P_i)\}\right|\right] \tag{1}$$

where, a_i, b_i, c_i, d_i and e_i are the cost coefficients of the i-th unit. P_i is the output power in MW at the t-th interval.

2.2. Problem constraints

- Unit capacity constraints

$$P_i^{\min} \le P_i \le P_i^{\max}, i = 1, \ldots, N \tag{2}$$

where, $P_i^{\min}$ and $P_i^{\max}$ are respectively, lower and upper generation limits of the i-th generator.

- Power balance constraint

$$\sum_{i=1}^{N} P_i - P_D - P_L = 0 \tag{3}$$

where, P_D is total demand power. P_L is the total system losses calculated using the following constant loss formula (Basu, 2006).

$$P_L = \sum_{i=1}^{N}\sum_{j=1}^{N} P_iB_{ij}P_j + \sum_{i=1}^{N} B_{oi}P_i + B_{oo} \tag{4}$$

where, B_{ij}, B_{oi}, B_{oo} are the loss-coefficient matrix.

- POZ constraints

The POZ constraints for the i-th unit due to the vibrations in the shaft are described in the following equation.

$$P_i \in \begin{cases} P_i^{\min} \le P_i \le P_{i,1}^{down} \\ P_{i,k-1}^{up} \le P_i \le P_{i,k}^{down} \quad , k = 2, \ldots, z_i \\ P_{i,z_i}^{up} \le P_i \le P_i^{\max} \end{cases} \tag{5}$$

where, z_i is the number of the POZs for the i-th unit. $P_{i,k}^{down}$ and $P_{i,k}^{up}$ are minimum and maximum limits of the k-th POZ, respectively.

By considering POZ constraints, the generator will have discontinuous input–output characteristics as shown in Fig. 1.

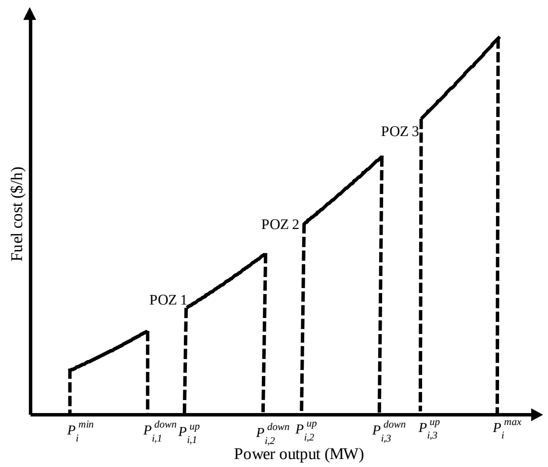

Fig. 1. Input-output characteristic.

3. Proposed optimization technique

3.1. Original ABC

ABC algorithm firstly introduced by Karaboga (2005) is one of the newest swarm-based techniques. Its main algorithm structure consists of four steps.

- Step 1: Initialization phase

ABC algorithms start by generating SN food sources and all algorithm parameters. Each food source $X^i = [x_1^i, x_2^i, \cdots, x_D^i]$ is considered as solution and it is generated randomly on the D-dimensional problem space as given by the following equation.

$$x_j^i = X_j^{min} + rand(0,1)(X_j^{max} - X_j^{min}) \tag{6}$$

Where, X_j^{min} and X_j^{max} are limits of the food source in dimension j.

The fitness function of each solution X^i that corresponds to the objective function is assumed as the nectar amount evaluated by an employed bee on the food source. It can be calculated as follows.

$$fit(X^i) = \begin{cases} \frac{1}{1+f(X^i)}, & f(X^i) \ge 0 \\ 1 + |f(X^i)|, & f(X^i) < 0 \end{cases} \tag{7}$$

where, f is the objective function.

- Step 2: Employed bees phase

Each employed bee tries to update each selected food source X^i in order to find better location close to this source. The updated food source V^i is determined as follows.

$$v_j^i = x_j^i + \varphi_j^i(x_j^i - x_j^k) \tag{8}$$

Indices k and j are chosen randomly from $\{1,2,\ldots,SN\}$ and $\{1,2,\ldots,D\}$, respectively. φ_j^i is a uniform real number in the range of [0,1].

- Step 3: Onlooker bees phase

In this step, each onlooker bee selects the food source based on the nectar amount. The probability of selection of a food source X^i is given in Eq. 9.

$$p_i = \frac{fit(X^i)}{\sum_{n=1}^{SN} fit(X^n)} \tag{9}$$

The selected food source will be update using Eq. 8. During this step, a greedy selection between V^i and X^i.

- Step 4: Scoot bees phase

If an onlooker that its food source cannot be improved in the last step, it will be converted to a scout bee and it starts to search another source using Eq. 6.

3.2. Modified ABC algorithm

The main drawback addressed to the classical ABC algorithm is the random selection of the j-th dimension in the employed and onlooker bees' phases. That allows decreasing the convergence speed and even providing a local optimum. Within this context, this paper proposes a new search method called local search technique. Instead of replacing the j-th dimension, the whole food source will be updated. The flowchart of the local search method applied in this study applied to update each food source is described in Fig. 2.

4. Simulation results

The proposed modified ABC algorithm with local search (ABC-LS) is validated using the benchmark test system compromising ten thermal units with valve-point loading effects and prohibited operating zones. The system data are taken from (Basu, 2008) and they are given in Table 1, 2, and 3. A comparison of the proposed technique with the classical ABC algorithm is presented in this section to demonstrate its effectiveness in finding the best optimum solution. The B-loss matrix of the ten-unit system is described in Eq. 10.

$$B = 10^{-4}\begin{bmatrix} 0.49 & 0.14 & 0.15 & 0.15 & 0.16 & 0.17 & 0.17 & 0.18 & 0.19 & 0.20 \\ 0.14 & 0.45 & 0.16 & 0.16 & 0.17 & 0.15 & 0.15 & 0.16 & 0.18 & 0.18 \\ 0.15 & 0.16 & 0.39 & 0.10 & 0.12 & 0.12 & 0.14 & 0.14 & 0.16 & 0.16 \\ 0.15 & 0.16 & 0.10 & 0.40 & 0.14 & 0.10 & 0.11 & 0.12 & 0.14 & 0.15 \\ 0.16 & 0.17 & 0.12 & 0.14 & 0.35 & 0.11 & 0.13 & 0.13 & 0.15 & 0.16 \\ 0.17 & 0.15 & 0.12 & 0.10 & 0.11 & 0.36 & 0.12 & 0.12 & 0.14 & 0.15 \\ 0.17 & 0.15 & 0.14 & 0.11 & 0.13 & 0.12 & 0.38 & 0.16 & 0.16 & 0.18 \\ 0.18 & 0.16 & 0.14 & 0.12 & 0.13 & 0.12 & 0.16 & 0.40 & 0.15 & 0.16 \\ 0.19 & 0.18 & 0.16 & 0.14 & 0.15 & 0.14 & 0.16 & 0.15 & 0.42 & 0.19 \\ 0.20 & 0.18 & 0.16 & 0.15 & 0.16 & 0.15 & 0.18 & 0.16 & 0.19 & 0.44 \end{bmatrix} \quad (10)$$

Two cases have been considered in this study.

Table 1
System data.

Unit	a	b	c	d	e	$P_i^{\min}$ (MW)	$P_i^{\min}$ (MW)	Prohibited zone (MW)
1	786.7988	38.5397	0.1524	450	0.041	150	470	[150 165], [448 453]
2	451.3251	46.1591	0.1058	600	0.036	135	470	[90 110], [240 250]
3	1049.9977	40.3965	0.0280	320	0.028	73	340	-
4	1243.5311	38.3055	0.0354	260	0.052	60	300	-
5	1658.5696	36.3278	0.0211	280	0.063	73	243	-
6	1356.6592	38.2704	0.0179	310	0.048	57	160	-
7	1450.7045	36.5104	0.0121	300	0.086	20	130	-
8	1450.7045	36.5104	0.0121	340	0.082	47	120	[20 30], [40 45]
9	1455.6056	39.5804	0.1090	270	0.098	20	80	-
10	1469.4026	40.5407	0.1295	380	0.094	10	55	[12 17], [35 45]

Table 2
Optimum solution without POZs constraints.

P_D (MW)	1000		1200		1400		1600	
Method	ABC-LS	ABC	ABC-LS	ABC	ABC-LS	ABC	ABC-LS	ABC
P_1 (MW)	150.3980	150.2608	50.1183	150.1993	150.1176	150.1631	150.2688	150.4402
P_2 (MW)	135.0000	135.0000	135.0000	135.0000	135.0000	135.0000	135.0000	135.0000
P_3 (MW)	73.8300	79.5581	182.6786	79.4907	190.8530	195.7603	298.3047	294.5893
P_4 (MW)	60.0000	60.0000	119.2166	173.3380	184.1652	181.3227	300.0000	300.0000
P_5 (MW)	172.0393	173.6729	172.4413	221.4741	242.5004	243.0000	231.0179	235.2401
P_6 (MW)	115.2207	139.9312	121.2681	123.1007	159.5337	156.8323	157.8854	157.8426
P_7 (MW)	130.0000	130.0000	129.4122	128.2707	130.0000	130.0000	129.4678	129.7292
P_8 (MW)	120.0000	120.0000	119.9208	119.1100	120.0000	119.9977	120.0000	120.0000
P_9 (MW)	52.0065	20.0000	52.2784	53.2920	79.5927	79.2334	80.0000	80.0000
P_{10} (MW)	10.0000	10.0000	43.7297	42.9229	43.4245	43.8966	44.3790	43.4682
Cost ($/h)	59380.69	59413.58	68987.01	69111.71	79593.61	79650.95	91123.12	91128.65
losses (MW)	18.4943	18.4230	26.0641	26.1984	35.1870	35.2061	46.3235	46.3095

Table 3
Optimum solution with POZs constraints.

P_D (MW)	1000		1200		1400		1600	
Method	ABC-LS	ABC	ABC-LS	ABC	ABC-LS	ABC	ABC-LS	ABC
P_1 (MW)	65.1204	165.1523	165.2710	165.1318	165.0909	165.0722	166.6105	165.3441
P_2 (MW)	35.0000	135.0000	135.0000	135.1689	135.0734	135.0000	135.0000	135.0000
P_3 (MW)	76.5427	74.1883	173.3861	86.3128	199.5952	189.7696	295.6962	302.1017
P_4 (MW)	64.9224	133.8604	124.3907	180.6893	182.8316	181.9040	300.0000	266.8232
P_5 (MW)	173.8728	73.0000	228.8840	229.2110	223.6764	222.9506	243.0000	242.3350
P_6 (MW)	123.1177	122.6770	122.9827	123.1096	159.8934	159.2527	159.6806	159.7217
P_7 (MW)	130.0000	130.0000	127.9262	130.0000	129.2105	129.5609	129.6302	129.8065
P_8 (MW)	120.0000	120.0000	117.4995	119.4790	120.0000	119.9245	119.1480	120.0000
P_9 (MW)	20.0000	54.5960	20.8457	47.1720	74.5740	79.2713	52.1945	79.9178
P_{10} (MW)	10.0000	10.0000	10.0000	10.0000	45.3529	52.6214	45.4802	45.3456
Cost ($/h)	60140.41	60726.68	70003.49	70024.86	80447.9	80499.54	91921.37	92055.08
losses (MW)	18.5759	18.4740	26.1858	26.2744	35.2982	35.3272	46.4403	46.3956

4.1. Case 1: Without POZs constraints

Fig. 3 shows the convergence of the total cost for total demand power of 1000 MW using ABC-LS and ABC algorithms. It is evident that the proposed algorithm gives the best solution. It can be seen that the minimum total cost when using ABC-LS is 59380.69 $/h, while it is 59413.58 $/h for classical ABC.

Optimum solutions for various loads are given in Table 2. Form this table; it is clear that the ABC-LS provided the best results for all loads.

4.2. Case 2: With POZs constraints

In this case, POZs constraints have been considered in the ED problem. Optimum generated powers obtained using ABC-LS and ABC algorithms are depicted in Table 3. It is observed that the proposed method outperforms the classical ABC.

In order to examine the impact of POZs constraints on the ED problem solution, the variation of the difference ΔC between costs obtained using the proposed algorithm for the cases with and without POZs, versus various loads has been illustrated in Fig. 4. It can be seen that ΔC is positive for all loads. Thus, we can conclude that when POZs are included in the problem, the optimum cost increases due to the limitation of the search space.

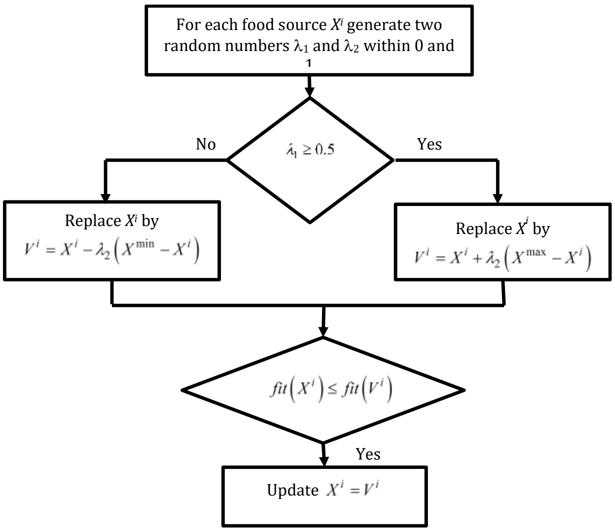

Fig. 2. Local search method.

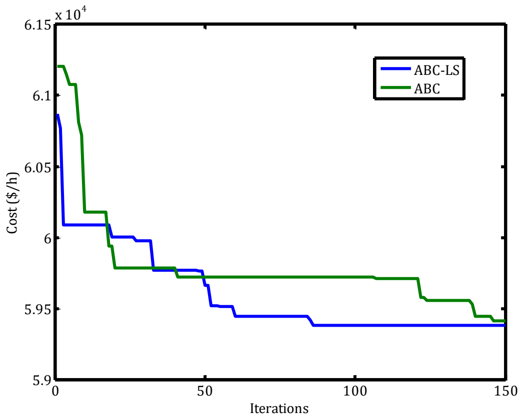

Fig. 3. Cost convergence for PD = 1000 MW.

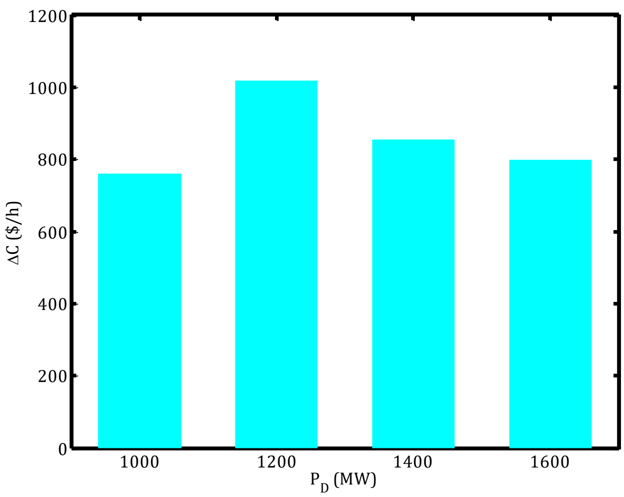

Fig. 4. Effect of POZs on the optimum cost.

5. Conclusion

In this paper a new artificial bee colony (ABC) based approach is proposed to solve the non-smooth and non-convex economic power dispatch (EPD). This technique combines the ABC algorithm and a local search method in order to improve the exploration of the search space. The EPD problem has been converted in to a mono-objective optimization problem that aims to minimize total production cost. Valve-point loading effects, total power losses and other operating constraints have been considered. The mentioned problem is solved with and without considering prohibited operating zones.

Simulations results are carried out using the ten-unit system for various loads. It is observed that:

- The optimum cost increase when POZs have been considered due to the reduction of the search space.
- The new technique outperforms the original ABC algorithm.

References

Bakirtzis A, Petrides V, and Kazarlis S (1994). Genetic algorithm solution to the economic dispatch problem. IEE Proceedings Generation Transmission and Distribution, 141(4): 377-382. https://doi.org/10.1049/ip-gtd:19941211

Basu M (2006). Particle swarm optimization based goal-attainment method for dynamic economic emission dispatch. Electric Power Components and Systems, 34(9): 1015-1025. https://doi.org/10.1080/5325000600596759

Basu M (2008). Dynamic economic emission dispatch using nondominated sorting genetic algorithm-II. Electric Power and Energy Systems, 30(2): 140-149. https://doi.org/10.1016/j.ijepes.2007.06.009

Bouzeboudja H, Chaker A, Allali A, and Naama B (2005). Economic dispatch solution using a real-coded genetic algorithm. Acta Electrotechnica et Informatica, 5(4): 1-5.

Chen CL and Wang SC (1993). Branch-and-bound scheduling for thermal generating units. IEEE Transactions on Energy Conversion, 8(2): 184-189. https://doi.org/10.1109/60.222703

Elaiw AM, Xia X, and Shehata AM (2013). Combined heat and power dynamic economic dispatch with emission limitations using hybrid DE-SQP method. Abstract and Applied Analysis, 2013: Article ID 120849, 10 pages. https://doi.org/10.1155/2013/120849

Gar CW, Aganagic JG, Tony Meding Jose B, and Reeves S (2001). Experience with mixed integer linear programming based approach on short term hydrothermal scheduling. IEEE Transaction on Power Systems, 16(4): 743-749. https://doi.org/10.1109/59.962421

Jadoun VK, Gupta N, Niazi KR, and Swarnkar A (2014). Nonconvex economic dispatch using particle swarm optimization with time varying operators. Advances in Electrical Engineering, 2014: Article ID 301615, 13 pages. https://doi.org/10.1155/2014/301615

Jain P, Swarnkar KK, Wadhwani S, and Wadhwani AK (2012). Prohibited operating zones constraint with economic load dispatch using genetic algorithm. International Journal of Engineering and Innovative Technology, 1(3): 179-183.

Jasper J and Aruldoss AVT (2013). Deterministically guided differential evolution for constrained power dispatch with prohibited operating zones. Archives of Electrical Engineering, 62(4): 593-603. https://doi.org/10.2478/aee-2013-0047

Jianga S, Jia Z, and Shen Y (2014). A novel hybrid particle swarm optimization and gravitational search algorithm for solving economic emission load dispatch problems with various practical constraints. Electrical Power and Energy Systems, 55: 628-644. https://doi.org/10.1016/j.ijepes.2013.10.006

Karaboga D (2005). An idea based on honey bee swarm for numerical optimization (Tech. Rep TR06). Computer Engineering Department, Kayseri, Turkey. Available online at: https://pdfs.semanticscholar.org

Kherfane RL, Younes M, Kherfane N, and Khodja F (2014). Solving economic dispatch problem using hybrid GA-MGA. Energy Procedia, 50: 937-944. https://doi.org/10.1016/j.egypro.2014.06.112

Labbi Y, Ben Attous J, and Mahdad B (2014). Artificial bee colony optimization for economic dispatch with valve point effect. Frontier Energy, 8(4): 449-458. https://doi.org/10.1007/s11708-014-0316-8

Lin CE, Chen ST, and Huang CL (1992). A direct Newton-Raphson economic dispatch. IEEE Transactions on Power Systems, 7(3): 1149-1154. https://doi.org/10.1109/59.207328

Park JB, Lee KS, Shin JR, and Lee KY (2005). A particle swarm optimization for economic dispatch with nonsmooth cost functions. IEEE Transaction on Power Systems, 20(1): 34-42. https://doi.org/10.1109/TPWRS.2004.831275

Ramesh V, Jaybarathi T, Mital S, Asthana S, and Basu S (2010). Combined hybrid differential particle swarm optimization approach for economic dispatch problems. Electric Power Components and Systems, 38(5): 545-557. https://doi.org/10.1080/15325000903376958

Sen T and Mathur HD (2016). A new approach to solve Economic Dispatch problem using a Hybrid ACO–ABC–HS optimization algorithm. Electrical Power and Energy Systems, 78: 735-744. https://doi.org/10.1016/j.ijepes.2015.11.121

Tlijani K, Guesmi T, and Abdallah HH (2017). Dynamic coupled active–reactive dispatch including SVC devices with limited switching operations. Arabian Journal for Science and Engineering, 42(7): 2651-2661. https://doi.org/10.1007/s13369-016-2286-0

Wood AJ and Wollenberg BF (2012). Power generation, operation, and control. John Wiley and Sons, New York, USA.

Yang Z, Li K, Niu Q, Xue Y, and Foley A (2014). A self-learning TLBO based dynamic economic/environmental dispatch considering multiple plug-in electric vehicle loads. Journal of Modern Power Systems and Clean Energy, 2(4): 298-307. https://doi.org/10.1007/s40565-014-0087-6