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Power search algorithm (PSA) for combined economic-emission dispatch problems considering valve point effects in economic load dispatch

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Abstract: Economic load dispatch has become the prime and major concern in power system networks. Use of nonrenewable fuels as an input to power systems results in toxic gas emission and depletion of resources for future generations. Allocation of optimal power to generators serves as a solution to this issue. The suggested power search algorithm (PSA) is a novel solution for the reduction of the fuel cost, emissions, and power loss. This algorithm searches its solution inside the search space from minimum to maximum in case of forward search. The global optimum solution is obtained with much less execution time compared to different optimization algorithms. The robustness of the PSA is tested with various IEEE test systems. The proposed PSA proves to be better than the existing algorithms.

Key words: Combined economic-emission dispatch, economic load dispatch, power search algorithm, valve-point loading

1. Introduction

The basic and major requirement of economic load dispatch (ELD) is minimizing the fuel cost by operating generators within specified constraints. The combination of fuel cost and emission is the combined economic-emission dispatch (CE-ED). This is categorized under multiobjective optimization, since reducing fuel cost and emission takes place simultaneously. The fuel's calorific value is inferior, resulting in high toxic gas emissions. The toxic gas has ill effects on plants, animals, and human beings. Many algorithms have been proposed over the decades for ELD and CE-ED problems. The present PSA was evaluated in three IEEE standard test systems. Comparisons were carried out for the proposed PSA and other algorithms. The objective satisfied by the PSA is given in Section 2. The problem formulation is elucidated in Section 3. PSA is discussed in Section 4. Results and discussion are explained in Section 5. The conclusion is summarized in Section 6.

2. Related works

The improved-particle swarm optimization [1] was illustrated to solve ELD problems with valve-point loading (VPL) effects integrating PSO with chaotic sequences. In this method, PSO increases the space for searching local optimal points and chaotic-sequence eliminates the local optima. A novel scheme of coding was developed for solving ELD problems with help of hybrid algorithm with simulated annealing (SA) and PSO [2]. A separate memory space was allocated for the best particle in the improved coordinated-aggregation–based PSO

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[3] algorithm. For solving the economic dispatch (ED) problem combined with VPL, a novel PSO [4] combined with the direct search method was advised. The self-adaptive differential evolution (DE) [5] was advised to unravel ELD with VPL effects. Cross-over constant and weight are the mandatory parameters of control in the DE algorithm that are randomly applied to the differential function. This methodology eliminates impossible solutions and increases an algorithm's potency.

An artificial bee colony (ABC) algorithm [6] was developed for resolving the ELD issues in coordination with nonsmooth cost functions. It is an optimization technique that depends on honeybee foraging behavior. A self-adaptive–real-coded genetic algorithm [7] and an improved taboo search [8] were developed to solve the ELD problems along with VPL effects. To unravel the convex and nonconvex ELD problems, a biogeography-based optimization (BBO) [9] algorithm was formulated, which depends on the biological species that are geographically distributed. An approach named novel seeker optimization algorithm [10] was developed to solve ELD problems. For obtaining optimization, the capability of human search takes place and their understanding has been exploited. In addition, the evaluation of the response to the change in position of the particle decides the search direction and a simple fuzzy rule finalizes the step length.

The combination of DE and interior point method (IPM), i.e. DE-IPM [11], was developed for solving the ELD problem along with VPL. Initially, for the minimization of cost function, IPM is involved without considering the VPL, whereas in the second stage, VPL is considered and DE plays the role of cost function minimization. A study on CE-ED problems for the minimization of fuel cost and emissions takes place simultaneously and the efficiency of the GA-PSO [12] was discussed. The application of a flower pollination algorithm (FPA) inspired by flowering plants' pollination process [13] for the CE-ED problems has been discussed. Self-pollination and cross-pollination are ways of achieving pollination. The application of a firefly algorithm (FA) [14] for solving ELD and CE-ED problems was illustrated for different test cases and the comparison of results carried out with heuristic algorithms. A genetic algorithm based on similarity crossover methodology [15] was proposed for solving the CE-ED load problems, where the children are formed by the relationship between the father and mother chromosome relationship.

Glow worm swarm optimization [16] was developed and applied to the CE-ED problems, where the glow worms act as agents for finding the optimal path in the entire search space. A global search algorithm, namely cuckoo search algorithm (CS) [17], was formulated to obtain global solutions for the CE-ED problems, where the characteristics depend upon the strategic breeding of cuckoo species that lay their eggs in host birds' nest. The nest here refers to the potential solution obtained. Improved cuckoo search (ICS) [18] was developed with an objective of acquiring the best global solution for CE-ED problems, where certain modifications in the original case were carried out. Modified ABC (MABC) [19] was formulated by introducing a new mutation evolved from DE for improving the exploitation process. An SA algorithm [20] was developed with the concept of introducing a new decision variable and the optimal generations for the purpose of obtaining the best solution.

Parallel synchronous PSO (PSPSO) [21] was developed for better convergence, in which the time requirement is taken into consideration for parallel evaluation of particles and at the end of all the iterations, the position and velocity update takes place. This results in obtaining better results for CE-ED problems. The combination of PSO and the probability functions related to Gaussian functions and/or chaotic sequences [22] was presented for the purpose of solving ELD problems. The opposition-based harmony search (OHS) [23] algorithm was developed to obtain a better optimal solution for CE-ED problems. The OHS algorithm employs the technique of opposition-based learning methodology for the initialization of harmony memory and for the process of jumping generation. Based on the Pareto optimal set, fuzzified ABC [24] was formulated to determine the best compromising solution for CE-ED problems. The gravitational search algorithm (GSA) [25] was formulated based on the physical laws of gravity and laws of motion, where two different objective functions are combined into a single objective function. The opposition-based GSA [26] was developed for acquiring the best results with a faster convergence rate. Considering the variance variable probability, the constrained globalized Nelder–Mead [27] algorithm was developed recently for solving ELD problems neglecting valve point effects. The Hopfield modeling framework (HFM) [28] was introduced with an energy function that comprises energy function, total fuel cost, and the transmission line losses defined for obtaining the optimal solution for the economic dispatch problems. BBO [29] was formulated with the characteristics of geographical distribution of biological species and was implemented for various sections of the ELD problems. The symbiotic organisms search (SOS) [30] optimization algorithm for CE-ED was developed with the aim of reducing fuel and emission costs simultaneously. The SOS algorithm depends upon the characteristics of long-time interactions with other living beings and togetherness. The proposed PSA-FSA is good at identifying the global optimum solution for CE-ED problems when compared to the other algorithms.

3. Problem formulation

3.1. ELD

Power generation based on fossil fuels results in high toxic effluents and the fuel cost incurred is also very high. The minimization of fuel cost is the main objective of the ELD. The objective of this function is expressed with Eq. (1).

$$MinF_t = \sum_{i=1}^{N} F_{1i}(P_i), \tag{1}$$

where $F_{1i}(P_i)$ is the fuel cost equation of the ith generator, discussed in Eq. (2).

$$F_t = \sum_{i=1}^{N} a_i Pi^2 + b_i P_i + c_i, \tag{2}$$

where N refers to the total number of generators of a power plant, the fuel cost coefficients of the generator i are denoted as a_i, b_i, and c_i and the output power from the generator i is referred to as P_i.

3.2. Emission

In addition to the reduction of fuel cost, fossil fuel emissions also need to be minimized. Eq. (3) describes the objective function of the emission.

$$Min \sum_{i=1}^{N} F_{2i}(P_i) = \sum_{i=1}^{N} f_i P_i^2 + e_i P_i + d_i, \tag{3}$$

where the entire emission cost is denoted by $F_{2i}(P_i)$; f_i, e_i, and d_i are the emission cost coefficients of the ith generator and P_i is the output power from the generator i.

3.3. CE-ED

The objective function of the CE-ED problem is defined as follows:

$$MinF_t \sum_{i=1}^{N} F_i = \sum_{i=1}^{N} (F_{1i}(P_i) + F_{2i}(P_i)), \tag{4}$$

where F_t is the total cost, $F_{1i}(P_i)$ is the fuel cost equation, and $F_{2i}(P_i)$ is the total emissions cost.

4. PSA

PSA is a direct search method for determining the power output and the fuel cost for ELD problems. Forward-based search technique or forward search approach (FSA) is carried out in the proposed algorithm for determining the optimal solution for the CE-ED problems. In this approach, the power output for the ith generator is given in following equation:

$$P_i = P_i^{\min} * (1 + k + k^2), \tag{5}$$

where P_i is the output power of the generator $i, P_i^{\min}$ is the minimum power generation limit for the generator i, and k is a numerical variable. The range for k starts from 0 and increases at increments of 0.001. For maintaining the power demand (P_D), a power balance constraint is introduced. Eq. (6) describes the aforesaid constraint.

$$P_i = P_D + P_L - \sum_{\substack{i=1 \\ j\neq i}}^{N} P_j, \tag{6}$$

where P_L is the transmission loss in the power system. The quadratic function $(1 + k + k^2)$ will give a systematic increment for the output power of each machine and also the number of maximum iteration for the problem is fixed by k. The PSA was tested in various IEEE standard test systems with several trial runs and the maximum value of k was fixed at 2.

4.1. Pseudocode for FSA

```
Begin
Read $P_D$, $P_i^{\min}$,$P_i^{\max}$, fuel cost, emission and loss coefficients
Initialize $k$ and $T_{c\,(\min)}$
Vary $x$ from 0 to 2
For each $x$ value, calculate $P_i$
if $P_i \leq P_i^{\min}$, then fix $P_i = P_i^{\min}$
if $P_i \geq P_i^{\max}$, then fix $P_i = P_i^{\max}$
Calculate $P_L$
Put $k = 1$ (for unit 1)
Redefine $Pk = P_D + P_L \sum_{\substack{j=1 \\ j\neq k}}^{N} P_j$
Calculate fuel cost and emission
Determine $T_{cn\,(\min)}$
If $T_{cn\,(\min)} > T_{c\,(\min)}$, then redefine $T_{c\,(\min)}$
Repeat steps 4 to 13 for all units
Determine redefined $T_{c\,(\min)}$ for all units
Notify $P_D$, $P_L$, fuel cost, and emission
End
```

5. Simulation results and discussion

The proposed PSA-FSA was validated for 3 different standard IEEE bus systems in the MATLAB 2012 environment. The following are the system specifications: Windows 10 operating system, with Intel Core

i3-5005U CPU @ 2.00 GHz processor. The standard IEEE test systems were as follows:
Case Study 1: IEEE 3 unit system with power demand (P_D) = 400, 550, and 700 MW
Case Study 2: IEEE 30 bus system (6 unit) with P_D = 500, 600, 700, 800, 900, and 1100 MW (without losses)
Case Study 3: IEEE 20 unit system with P_D = 2500 MW
Case Study 4: IEEE 30 bus system (6 unit) with P_D = 500, 700, 900, and 1 MW (with losses)
Case Study 5: IEEE 30 bus system (6 unit) with P_D = 1000 MW (without loss)
Tables 1 to 6 illustrate the simulated results for the proposed approach compared with various algorithms.

5.1. Case study 1

In this study, an IEEE 3 unit system with P_D = 400, 550, and 700 MW was considered with losses. The data for the 3 unit system are taken from [13]. The performance of PSA-FSA and its comparison with various algorithms are given in Table 1. Comparing the proposed PSA-FSA with GA, PSO, and FPA at P_D = 400 MW, fuel cost was reduced by 77.315, 78.154, and 77.105 \$/h, emissions were reduced by 2.915, 3.385, and 0.8738 kg/h, and the total power loss was reduced by 1.50524, 1.50373, and 1.5046 MW, respectively. Similarly, when compared with PSPSO, CS, and ICS, fuel cost decreased by 76.615, 76.495, and 87.1007 \$/h and emissions were reduced by 0.88, 0.8898, and 0.82 kg/h, respectively. Power loss is not reported for PSPSO, CS, and ICS algorithms. Comparing the proposed approach with GA, PSO, PSPSO, and CS for P_D = 550 MW, fuel cost was reduced by 154.91, 157.114, 154.15, and 153.78 \$/h, respectively. On comparing the proposed approach with GA, PSO, PSPSO, and CS for P_D = 700 MW, fuel cost and emissions were reduced by 268.404 \$/h and 12.541 kg/h, 270.076 \$/h and 12.778 kg/h, 266.674 \$/h and 10.859 kg/h, and 266.594 \$/h and 10.8624 kg/h, respectively. Analyses for P_D = 550 and 700 MW were not carried out by the authors of FPA and ICS. In addition, for P_D = 550 and 700 MW, power losses were not reported for any of the methods reported for comparison.

Table 1. Solution for CE-ED problem for three unit system considering losses with the proposed approach.

P_D (MW)	Performance	GA [13]	PSO [13]	FPA [13]	PSPSO [21]	CS [17]	ICS [18]	PSA-FSA
400	Fuel cost	20,838.31	20,839.149	20,838.1	20,837.61	20,837.49	20,848.0957	20,760.995
	Emissions	202.265	202.735	200.2238	200.23	200.2398	200.170	199.35
	P_L (MW)	7.41324	7.41173	7.4126	NR	NR	NR	5.908
550	Fuel cost	27,905.11	27,907.314	NA	27,904.35	27,903.98	NA	27,750.2
	Emission	383.614	384.361	NA	381.21	381.2174	NA	376.927
	P_L (MW)	NR	NR	NR	NR	NR	NR	11.024
700	Fuel cost	35,465.39	35,467.062	NA	35,463.66	35,463.58	NA	35,196.986
	Emissions	653.267	653.504	NA	651.585	651.5884	NA	640.726
	P_L (MW)	NR	NR	NR	NR	NR	NR	17.729

5.2. Case study 2

In this case study, an IEEE 30 bus system (6 unit system) with P_D = 500, 600, 700, 800, 900, and 1100 MW was considered, neglecting losses. The data for the 6 unit system for power demands ranging from 500–1100 MW are taken from [15]. Table 2 elucidates the results obtained by the proposed PSA-FSA for 6 unit system with various power demands ranging from 500–1100 MW. The best fuel costs and emissions obtained by the proposed PSA-FSA were 27,071.67 and 259.249 for 500 MW; 31,552.08 and 333.233 for 600 MW; 6159.24 and

429.426 for 700 MW; 40,890.56 and 545.879 for 800 MW; 45,662.67 and 662.977 for 900 MW; and 55,499.71 and 990.649 for 1100 MW, respectively. The fuel cost is described in \$/h and emissions are given in kg/h.

Table 2. Solution for CE-ED problem for six unit system neglecting losses with the proposed approach.

P_D (MW)	Performance	$\gamma-$iteration [17]	Recursive [17]	PSO [17]	DE [17]	CS [17]	PSA-FSA
500	Fuel cost	27,092.5	27,092.5	27,092.5	27,098.1	27,092.5	27,071.67
	Emissions	261.635	261.634	262.225	261.859	261.634	259.249
600	Fuel cost	31,628.7	31,628.6	31,634.9	31,629.2	31,628.6	31,552.08
	Emissions	338.993	338.992	339.82	339.065	338.992	333.233
700	Fuel cost	36,314	36,313.9	36,341.2	36,314	36,313.9	36,159.24
	Emissions	434.38	434.38	434.605	434.453	434.38	429.426
800	Fuel cost	41,148.4	41,148.3	41,160.3	41,152.6	41,148.3	40,890.56
	Emissions	547.797	547.796	547.844	547.802	547.796	545.879
900	Fuel cost	46,131.8	46,131.8	46,160.6	46,152.6	46,131.8	45,662.67
	Emissions	679.241	679.241	679.724	679.283	679.241	662.977
1100	Fuel cost	56,546.4	56,546.2	56,556.7	56,546.6	56,546.2	55,499.71
	Emissions	996.224	996.218	996.672	996.222	996.218	990.649

5.3. Case study 3

A test system consisting of 20 generating units with a power demand of 2500 MW considering losses without valve point effects was analyzed. The input data for the system are taken from [22]. The emission coefficient of the 20 generating units is taken from [23]. The best solution yielded by the proposed approach is presented in Table 3. Fuel and emissions costs yielded by the PSA-FSA approach were 62,138.87 \$/h and 27,290.25 t/h, respectively. In addition, the total loss was 82.27 MW, which was 9.34 MW less than the OHS algorithm, 9.33 MW less the BBO algorithm, 9.69 MW less than the HFM, and 9.7 MW less than the lambda iteration method. The results obtained by the proposed approach for the minimization of fuel cost, emissions, and total loss were the promising ones.

5.4. Case study 4

In this case study, an IEEE 6 unit system with $P_D = 500$, 700, and 900 MW was analyzed and the robustness of the algorithm was determined by comparing the data from BBO and SOS algorithms. Table 4 displays the results obtained by the proposed approach. Fuel cost, emissions, and power loss were reduced compared with the BBO and SOS algorithms. The best fuel cost, emissions, and power loss obtained by the proposed PSA-FSA were, respectively, 27,389.677 \$/h, 276.628 kg/h, and 0.631 MW for 500 MW; 37,083.43 \$/h, 425.465 kg/h, and 1.465 MW for 700 MW; and 45,757.976 \$/h, 852.976 kg/h, and 2.861 MW for 900 MW. Table 5 shows the results obtained with the help of proposed approach for a power demand of 1 MW. The simulated results are compared with the FA [14] and GA-SQP [14]. The total cost was reduced by 19.547 \$/h with FA and 19.227 \$/h with GA-SQP. The power loss obtained by the proposed approach is 0.000058 MW, which is 0.0001 MW less than FA and 0.001538 MW less than GA-SQP. When emissions are considered, the PSA-FSA approach is 0.009 MW higher than the FA and 0.013 MW higher than GA-SQP.

Table 3. Simulation and comparison results for IEEE 20 machine system for the FSA compared with LI, HFM, BBO, and OHS for $P_D = 2500$ MW.

Generation (MW)	LI [28]	HFM [28]	BBO [29]	OHS [23]	PSA-FSA
G1	512.7805	512.7804	513.0892	511.8518	599.963
G2	169.1033	169.1035	173.3533	151.9528	115.25
G3	126.8898	126.8897	126.9231	111.3158	115.25
G4	102.8657	102.8656	103.3292	102.1659	115.25
G5	113.6836	113.6836	113.7741	103.6150	115.25
G6	73.5710	73.5709	73.06694	71.3042	46.1
G7	115.2878	115.2876	114.9843	114.2378	57.625
G8	116.3994	116.3994	116.4238	105.7168	115.25
G9	100.4062	100.4063	100.6948	118.5139	115.25
G10	106.0267	106.0267	99.99979	103.3803	69.15
G11	150.2394	150.2395	148.977	171.4014	230.501
G12	292.7648	292.7647	294.0207	313.3944	345.751
G13	119.1154	119.1155	119.5754	120.2281	92.2
G14	30.8340	30. 8342	30.54786	42.3455	46.1
G15	115.8057	115.8056	116.4546	145.3918	57.625
G16	36.2545	36.2545	36.22787	38.7053	46.1
G17	66.8590	66.8590	66.85943	47.4920	69.15
G18	87.9720	87.9720	88.54701	82.3015	69.15
G19	100.8033	100.8033	100.9802	82.7111	92.2
G20	54.3050	54.3050	54.2725	53.5811	69.15
Total generation (MW)	2591.9671	2591.9670	2592.1011	2591.6065	2582.265
Total loss (MW)	91.9670	91.9669	92.1011	91.6065	82.27
Total cost ($/h)	62,456.6391	62,456.6341	62,456.7926	62,340.00	62,138.874
Emission (kg/h)	NR	NR	NR	27,318.00	27,290.25

Table 4. Solution for CE-ED problem for six unit system including losses with the proposed approach.

P_D (MW)	Performance	BBO [29]	SOS [30]	PSA-FSA
500	Fuel cost ($/h)	28,456.29	28,454.31	27,389.677
	Emissions (kg/h)	277.728	277.773	276.628
	Loss (MW)	22.569	22.533	0.631
700	Fuel cost ($/h)	39,000.15	38,999.35	37,083.43
	Emissions (kg/h)	472.668	472.686	425.465
	Loss (MW)	38.429	38.415	1.465
900	Fuel cost ($/h)	49,615.07	49,615.05	45,757.79
	Emissions (kg/h)	857.081	857.133	852.976
	Loss (MW)	57.487	57.491	2.861

Table 5. Simulation results for IEEE 6 machine system for the PSA-FSA for $P_D = 1$ MW.

Power outputs	FA [14]	GA-SQP [14]	PSA-FSA
P_1 (MW)	0.050000	0.050000	0.050000
P_2 (MW)	0.147177	0.236700	0.050000
P_3 (MW)	0.099979	0.072500	0.050000
P_4 (MW)	0.434936	0.325200	0.750058
P_5 (MW)	0.214481	0.072500	0.050000
P_6 (MW)	0.052670	0.243100	0.050000
T_c ($/h)	603.354361	603.034045	583.806675
Emissions (kg)	0.236339	0.232184	0.245546
P_L (MW)	0.000158	0.001596	0.000058

Table 6. Solution for CE-ED problem for six unit system neglecting losses with the proposed approach compared with GSA ($P_D = 1000$ MW).

Generation (MW)	GSA [25]	PSA-FSA
$P1$ (MW)	78.8221	101.8
$P2$ (MW)	83.0013	22.72
$P3$ (MW)	164.2907	183.24
$P4$ (MW)	164.9136	171.024
$P5$ (MW)	258.1108	264.68
$P6$ (MW)	250.8619	256.536
Cost ($/h)	51,255.7880	51,153.14
Emissions (kg/h)	827.1380	818.827

5.5. Case study 5

In this case, a 6 unit system was considered for the power demand of 1000 MW. The result obtained by the proposed approach is compared with GSA. The best fuel cost and emission obtained by the proposed approach is 72.648 $/h and 8.311 kg/h less than GSA. The global optimum solution was obtained in a very short time and in fewer iterations. The proposed approach outperforms many algorithms reported in the literature.

6. Conclusion

In this article, a novel PSA is formulated for the CE-ED problems. The PSA-FSA has been simulated for IEEE 3, 6, and 20 unit standard test systems. The output obtained from the simulation is compared with the various existing algorithms. It is inferred that the proposed PSA is superior at solving the CE-ED problems considering VPL effects. Based on the results obtained, the PSA can be considered an efficient approach for solving CE-ED problems. In future, the proposed algorithm can be applied to a large area power system network by satisfying the necessary constraints.

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