Fuzzy logic controlled differential evolution to solve economic load dispatch problems

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Abstract

In recent years, soft computing methods have generated a large research interest. The synthesis of the fuzzy logic and the evolutionary algorithms is one of these methods. A particular evolutionary algorithm (EA) is differential evolution (DE). As for any EA, DE algorithm also requires parameters tuning to achieve desirable performance. In this paper tuning the perturbation factor vector of DE is done with a Fuzzy Logic Controller (FLC) that adjusts this parameter dynamically. We apply the fuzzy logic controlled differential evolution(FLC-DE) to solve the economic load dispatch problem of two test systems consisting of 13 and 40 thermal generators whose non-smooth fuel cost function takes into account the valve-point loading effects. Simulation results indicate that the performance of the FLC-DE present the best results when compared with other optimization approaches in solving economic load dispatch problems.

Keywords: *Differential Evolution, Economic Load Dispatch Problem, Fuzzy Logic Controller, Optimization*

1. Introduction

The economic dispatch problem is one of the important problems in operation and control of modern power systems. The most important thing in the economic load dispatch (ELD) of electric power generation is to schedule the generating unit outputs so as satisfy the load demand at minimum operating cost, while satisfying all unit and system equality and non-equality constraints. This makes the economic load dispatch problem a large-scale highly constrained nonlinear optimization problem [1]. In traditional ELD problems, the cost function of each generator is approximately represented by a simple quadratic function and the valve-points effects are ignored. These traditional ELD problems are solved using mathematical programming based on deterministic optimization techniques such as lambda iteration that has been applied through various software packages. A practical ELD must take valve point loading effects, multi fuel options [2] and prohibited operating zones [3] into consideration to provide the completeness for the ELD problem formulation. The resulting ELD is a non-convex optimization problem, which is a challenging and cannot be solved by the traditional methods.

Over the years, many efforts have been made to solve the ELD problem. In recent years, due to the power and simplicity of evolutionary algorithms, many researchers use these algorithms to solve ED problems.

Evolutionary algorithms such as genetic algorithm [4-11] and particle swarm optimization [12-20] have been implemented on the ELD problem. A particular evolutionary algorithm is differential evolution (DE). The DE algorithm has proposed by Storn and Price, and since then it has been used during many practical cases [21-24]. Many researchers such as Noman et al [25], Coelho et al[26] and Biswas et al[27] applied DE algorithm and modified versions of DE algorithm to solve ELD problems.
In spite of successful implementation of evolutionary algorithm, these algorithms have some weaknesses due to their stochastic nature that cause longer computation time and less guaranteed convergence. If we can control the parameters of evolutionary algorithm dynamically, we can reduce the randomness of these algorithms. The DE algorithm keeps all control parameters fixed during the optimization process; this feature is a weakness of DE. Due to the power of fuzzy control in variety of challenging control applications, in this paper, we propose the use of FLC to dynamically control the parameters of the DE algorithm. To judge the performance of the fuzzy logic controlled differential evolution (FLC-DE), we compared the results of the proposed method with DE and other popular optimization approaches.

The remainder of this paper is organized as follows. Section 2 describes the economic dispatch problem, while Section 3 explains the original DE algorithm. A fuzzy logic controller for DE is presented in section 4. Experimental results and comparisons are provided in Section 5. Last, Section 6 outlines the conclusion with a brief summary of results and future research.

2. Description of economic load dispatch problem

The aim of ELD problem is minimizing the total cost of generating units (the generator's fuel consumption and the operating cost) by determining the output power of each generating unit while all constraints of the system and the loads are satisfied[28,29].

a. Input-output characteristic of thermal units

The input - output characteristic for a thermal unit is called the cost function. The most simplified way to represent the cost function of each thermal unit is using a quadratic function, i.e.,

$$F(P) = aP^2 + bP + c \tag{1}$$

Where a, b, and c are given coefficients of the input - output characteristic. The coefficient c is related to the operating cost of a unit includes labor cost, maintenance cost and fuel transportation cost.
The output power of a generating unit is limited by the minimal and maximal capacity

$$P_{min} \leq P \leq P_{max} \tag{2}$$

b. Non-smooth ELD problem with valve points

The objective functions always have non-differentiable points due to valve point effects. A common way to take such effects into account is adding a sinusoidal function to the quadratic cost functions as follows [15-16][30]:

$$F(P) = aP^2 + bP + c + |e.\sin(f(P_{min} - P))| \tag{3}$$

Where e and f are the given coefficients of the generator.

c. Formulations of ELD problems

ELD optimization can be regarded as a minimization problem as follows [17-20]:

$$\text{minimize} \quad C = \sum_{i=1}^{n} F_i(P_i) \tag{4}$$

$$\text{subject to} \quad \begin{cases} \sum_{i=1}^{n} P_i = P_L + P_D \\ P_{i\,min} \le P_i \le P_{i\,max} \quad \text{for } i = 1,2,\dots,n \end{cases} \tag{5}$$

Where n, P_D and P_L are the number of generators, total demand of system and total line losses respectively. In this paper, we ignored the transmission losses, P_L; thus, $P_L = 0$.

d. ELD Constraints Handling

There are two constraints in the ELD problem, equality and inequality. Handling the inequality constraints is done simplicity by a simple check in optimization algorithm. The equality constraint of the ELD problem is considered in the Fitness function (fitfunc) by incorporating a penalty function (penfunc) as follow:

$$\text{penfunc} = \begin{cases} Q.\,|C - P_D| & \text{if } C < P_D \\ 0 & \text{else} \end{cases} \tag{6}$$

Where Q is a sufficently big constant, C is current total generating unit outputs and P_D is the total demand of system.

Therefore the objective of the problem is the minimization of generations cost and penalty function as defined by the equation 7.

$$\text{fitfunc} = \sum_{i=1}^{n} F_i(P_i) + \text{penfunc} \tag{7}$$

3. The original DE algorithm

In this section we give some background on the DE algorithm. DE is a population-based stochastic method for global optimization over continuous spaces [21-24], which can also work with discrete variables. The original version of DE can be defined by the following constituents.

1) The population

$$\begin{cases} P_{\boldsymbol{x},g} = (X_{i,g}), \;\; i = 1,2,\dots,Np, \;\; g = 1,2,\dots,g_{max} \\ \boldsymbol{x}_{i,g} = (x_{j,i,g}), \;\; j = 1,2,\dots,D \end{cases} \tag{8}$$

Where Np is the number of population vectors, g denotes the generation number, and D is the dimension of the problem, i.e. the number of parameters.

2) The initialization of the population

Each parameter of a population vector has a given domain is defined by its lower and upper bounds: $x_{j,low}, x_{j,upp}$; $j \in \{1,\dots,D\}$. The initial population is selected uniform randomly between the lower ($x_{j,low}$) and upper ($x_{j,upp}$) as follow:

$$x_{j,i,1} = rand_j(0,1).(x_{j,upp} - x_{j,low}) + x_{j,low} \tag{9}$$

The random number generator, rand j[0,1), returns a uniformly distributed random number from the range [0,1).

3) Mutation

By mutation for each population vector a mutant vector $V_{i,g}$ is created. One of the most popular DE mutation strategy is “rand/1/bin” [23-24]:

$$V_{i,g} = x_{r_1,g} + F.\left(x_{r_2,g} - x_{r_3,g}\right) \tag{10}$$

Where the indexes r_1, r_2, r_3 are selected (once per each mutation) random and different integers in the range $[1, NP]$ and also different from index i. F is an scalar namely amplification factor within the range [0.5, 1.0].

4) Crossover

The crossover uses parameters of the mutation vector $V_{i,G}$ and the target vector $x_{i,G}$ in order to create the trial vector $u_{i,G}$. The most popular form of crossover is uniform and is defined as[23,24]

$$\boldsymbol{u}_{i,g} = u_{j,i,g} = \begin{cases} v_{j,i,g} & if\left(rand_j(0,1) \le C_r \ or\ j = j_{rand}\right) \\ x_{j,i,g} & otherwise. \end{cases} \tag{11}$$

In equation 11($\ldots$ or $j = j_{rand}$) we are sure at least one component is taken from the mutation vector $V_{i,G}$. C_r is a critical parameter in diversity enhancement[23-24].

5) Selection

The vector with the lowest objective function value survives at least in next generation.

$$\boldsymbol{x}_{i,g+1} = \begin{cases} \boldsymbol{u}_{i,g} & if\ f(\boldsymbol{u}_{i,g}) \le f(\boldsymbol{x}_{i,g}) \\ \boldsymbol{x}_{i,g} & otherwise. \end{cases} \tag{12}$$

To reach termination condition, DE employs mutation, crossover and selection operations for each population vector.

4. Fuzzy Logic Controlled DE

There are several parameters in DE: the population size, NP, crossover control parameter, CR and the amplification factor of the difference vector, F. In this work, the population size and the crossover control parameter were fixed and we focused on the perturbation factor of the difference vector. In original DE, amplification factor, F, is a scalar but here we consider F a vector with size D that D is the dimension of the problem. We want to design a fuzzy logic controller (FLC) to control the amplification factor vector dynamically during the process of optimization. we used two point of view to describe the condition of DE’s population, population diversity (PD) and generation percentage (GP) so far performed. PD and GP used as inputs for the FLC. In this work, the PD in j-th dimension (PD_j) is given by:

$$PD_j = \frac{1}{NP\,(x_j^{max} - x_j^{min})} \sum_{i=1}^{NP} \sqrt{(x_{ij} - xb_j)^2} \tag{13}$$

Where x_j^{max} and x_j^{min} are minimum and maximum values of the j-th dimension, NP is the population size, and xb_j is the j-th parameter of the best solution in the population. We used from equation 14 to calculate the GP:

$$\mathrm{GP} = \frac{\mathrm{G}}{\mathrm{G}_{\max}} \tag{14}$$

Where G is the number of generations so far performed, and $\mathrm{G}_{\max}$ is the maximum generations of DE. Obviously, the range of PD, GP is in [0, 1].

Figure 1 depicted the generic shape of fuzzy membership function for the inputs and outputs of the FLC. The outputs of the FLC, control the perturbation factor and its range is [0, 0.3].

The designing and tuning the FLC is done manually based on our understanding of the DE's mechanism. The rule bases of FLC are shown in Table 1.

The FLC above described is applied to control the perturbation factor of the DE in *D* dimension. The flowchart of FLC-DE algorithm is depicted in Figure 2. Dashed rectangular in the figure shows the operation of FLC. The FLC dynamically controls the perturbation factor during the evolutionary process. Also, the FLC is fired 1 per 5 generations.

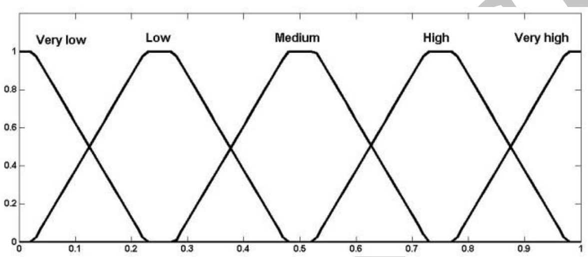

Figure 1. membership function for the inputs and output of the FLC

Table 1. The rule-base of the FLC. Very low, low, medium, high, very high and don't care are abbreviated as VL, L, M, H, VH and DC.

PD\GP	VL	L	M	H	VH
VL	H	DC	L	VL	VL
L	VH	VH	DC	L	VL
M	VH	VH	VM	DC	VL
H	VH	VH	VH	DC	VL
VH	VH	VH	VH	DC	L

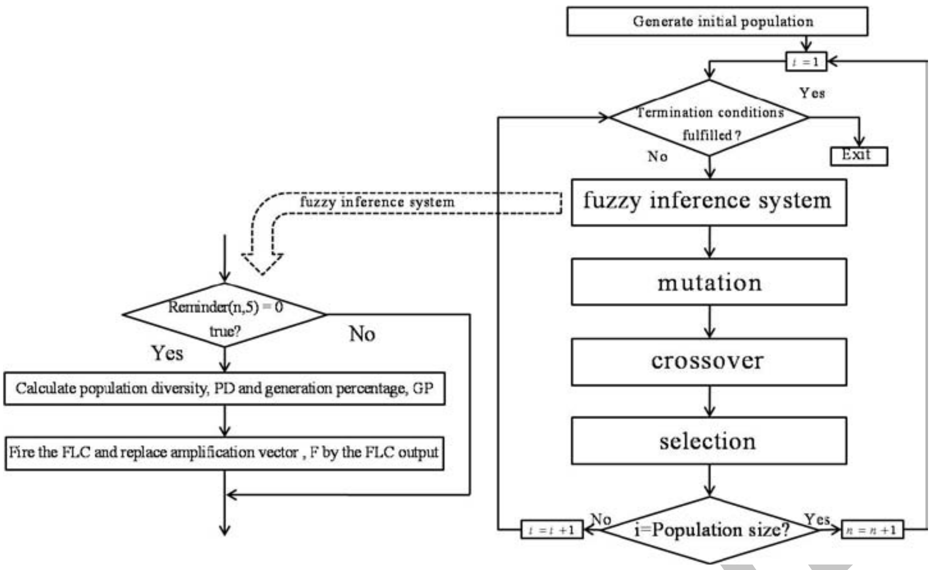

Figure 2. Flowchart of FLC-DE algorithm (sign "*" is the element-by-element multiplication)

5. Experimental result

In this section, we judge the performance of the FLC-DE approaches. We applied FLC-DE to two case studies of ELD problem with 13 and 40 thermal generators (units) and compared the results with those of Real Genetic Algorithm (RGA) [31], Particle Swarm Optimization (PSO)[31] and DE. In all cases, population size set to 70 (NP = 70) and maximum iteration for case study 1 and 2 was 1000 and 2500 respectively. In FLC-DE the Crossover control parameter for case studies 1 and 2 set as $\mathrm{CR} = 0.6$ and $\mathrm{CR} = 0.24$ respectively. In DE, the perturbation factor and the Crossover control parameter for case studies 1 and 2 set as $\mathrm{F} = 0.3$, $\mathrm{F} = 0.3$, $\mathrm{CR} = 0.6$ and $\mathrm{CR} = 0.24$ respectively. In RGA, the arithmetic crossover, the Gaussian mutation and the roulette wheel selection are used as described in [31]. In PSO, c1 = c2 = 1.2 and the inertia factor (w) is set as 0.72. Each optimization method implemented in MATLAB. In each case study, 30 independent runs are made for each of the optimization methods.

a. Case study 1

This system contains 13 thermal generating units with the effects of valve-point loading, as given in Table 2. The total load demand on the system is P_D = 1800MW. Parameters of this case study are reported in [32]. This EDP has many local minimum [26], so determination of the global minimum is not a simple work.

The results obtained for this case study are reported in Table 3 which shows the minimum, mean and the maximum fitness function achieved by the PSO, DE, RGA and FLC-DE approaches in last iterations. It can be evidently seen from table 3 that the FLC-DE succeeded in finding the best solution in the tested methods.

Table 4 gives the best result obtained by means of the FLC-DE with minimum cost of 17981.0084$/h. The progress of finding the average best solution by FLC-DE, DE, PSO and RGA over 30 independent runs for case study 1 is shown in Figure 3. According to this figure, although in the beginning of optimization, PSO export best solution, but local optimums trap PSO, DE and RGA and finally FLC-DE transcend from PSO algorithm and finds the best solution.

Table 2. Data for the 13 thermal units.

Thermal unit	$P_{i\,min}$	$P_{i\,max}$	a	b	c	e	f
1	0	680	0.00028	8.10	550	300	0.035
2	0	360	0.00056	8.10	309	200	0.042
3	0	360	0.00056	8.10	307	150	0.042
4	60	180	0.00324	7.74	240	150	0.063
5	60	180	0.00324	7.74	240	150	0.063
6	60	180	0.00324	7.74	240	150	0.063
7	60	180	0.00324	7.74	240	150	0.063
8	60	180	0.00324	7.74	240	150	0.063
9	60	180	0.00324	7.74	240	150	0.063
10	40	120	0.00284	8.60	126	100	0.084
11	40	120	0.00284	8.60	126	100	0.084
12	55	120	0.00284	8.60	126	100	0.084
13	55	120	0.00284	8.60	126	100	0.084

Table 3. Convergence results (the average of 30 independent runs) of DE, RGA, PSO and FLCDE for the case study with 13 thermal units.

Optimization method	Minimum cost ($/h)	Mean cost ($/h)	Maximum cost ($/h)
DE	18483. 4471	18484.0816	18485.6381
RGA	18421. 3083	18422.1418	18423.8371
PSO	18204. 0507	18204. 2163	18204. 7251
FLC-DE	**17981.0084**	17981.1201	17981.2023

Table 4. Best result (the average of 30 independent runs) obtained for the case study with 13 thermal units using FLC-DE.

Power	Generation (MW)	Power	Generation (MW)
$\mathbf{P_1}$	538.2813	P_8	109.9200
$\mathbf{P_2}$	149.7090	P_9	109.8684
$\mathbf{P_3}$	224.6815	P_{10}	40.4228
$\mathbf{P_4}$	109.6789	P_{11}	40.3674
$\mathbf{P_5}$	109.8653	P_{12}	55.0002
$\mathbf{P_6}$	109.9402	P_{13}	92.4024
$\mathbf{P_7}$	109.8794		
		$\sum_{i=1}^{13} P_i$	1800

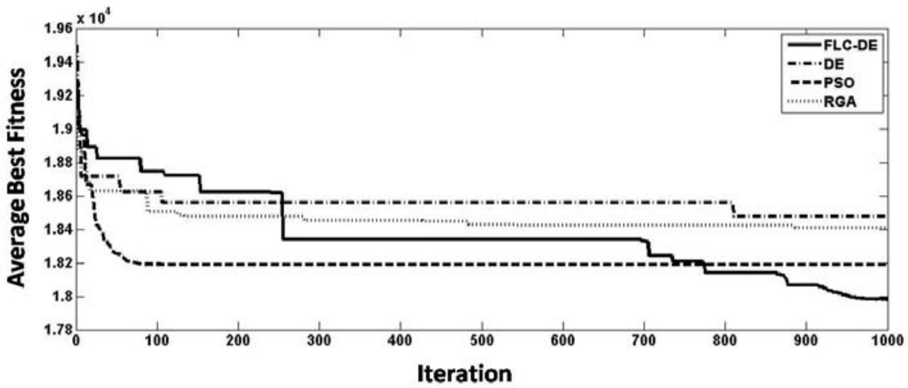

Figure 3. The progress of finding the average best solution by FLC-DE, DE, PSO and RGA over 30 independent runs for case study 1

b. Case study 2

This case study consists of 40 generating units with valve point loading as mentioned in [32]. Table 5 shows the parameters of this system. The total load demand on the system is P_D = 10500MW. Table 6 shows the minimum, mean and the maximum fitness function achieved by the PSO, DE, RGA and FLC-DE approaches. Table 6 clearly shows that the FLC-DE was the approach that obtained the best fuel cost for the EDP of 40 thermal units. Also, the best result obtained by means of the FLC-DE with minimum cost of 121523.34$/h is given in Table 7.

Figure 4 shows the progress of finding the average best solution by FLC-DE, DE, PSO and RGA over 30 independent runs for case study 2. According to this figure, FLC-DE tends to find the best solution faster than other algorithms and hence has a higher convergence rate. Also, local optimums cannot trap FLC-DE.

Table 5. Data for the 40 thermal units.

Thermal unit	$P_{i\,min}$	$P_{i\,max}$	a	b	c	e	f
1	36	114	0.00690	6.73	94.705	100	0.084
2	36	114	0.00690	6.73	94.705	100	0.084
3	60	120	0.02028	7.07	309.54	100	0.084
4	80	190	0.00942	8.18	369.03	150	0.063
5	47	97	0.01140	5.35	148.89	120	0.077
6	68	140	0.01142	8.05	222.33	100	0.084
7	110	300	0.00357	8.03	278.71	200	0.042
8	135	300	0.00492	6.99	391.98	200	0.042
9	135	300	0.00573	6.60	455.76	200	0.042
10	130	300	0.00605	12.90	722.82	200	0.042
11	94	375	0.00515	12.90	635.20	200	0.042
12	94	375	0.00569	12.80	654.69	200	0.042
13	125	500	0.00421	12.50	913.40	300	0.035
14	125	500	0.00752	8.84	1760.4	300	0.035
15	125	500	0.00708	9.15	1728.3	300	0.035
16	125	500	0.00708	9.15	1728.3	300	0.035
17	220	500	0.00313	7.97	647.85	300	0.035
18	220	500	0.00313	7.95	649.69	300	0.035
19	242	550	0.00313	7.97	647.83	300	0.035
20	242	550	0.00313	7.97	647.81	300	0.035
21	254	550	0.00298	6.63	785.96	300	0.035
22	254	550	0.00298	6.63	785.96	300	0.035
23	254	550	0.00284	6.66	794.53	300	0.035
24	254	550	0.00284	6.66	794.53	300	0.035
25	254	550	0.00277	7.10	801.32	300	0.035
26	254	550	0.00277	7.10	801.32	300	0.035
27	10	150	0.52124	3.33	1055.1	120	0.077
28	10	150	0.52124	3.33	1055.1	120	0.077
29	10	150	0.52124	3.33	1055.1	120	0.077
30	47	97	0.01140	5.35	148.89	120	0.077
31	60	190	0.00160	6.43	222.92	150	0.063
32	60	190	0.00160	6.43	222.92	150	0.063
33	60	190	0.00160	6.43	222.92	150	0.063
34	90	200	0.00010	8.95	107.87	200	0.042
35	90	200	0.00010	8.95	107.87	200	0.042
36	90	200	0.00010	8.62	116.58	200	0.042
37	25	110	0.01610	5.88	307.45	80	0.098
38	25	110	0.01610	5.88	307.45	80	0.098
39	25	110	0.01610	5.88	307.45	80	0.098
40	242	550	0.00313	7.97	647.83	300	0.035

Table 6. Convergence results (the average of 30 independent runs) of DE, RGA, PSO and FLCDE for the case study with 40 thermal units.

Optimization method	Minimum cost ($/h)	Mean cost ($/h)	Maximum cost ($/h)
RGA	126735.10	126758.31	126787.06
PSO	124115.26	124130.12	124139.72
DE	121603.61	121614.54	121621.73
FLC-DE	**121523.34**	121529.58	121531.29

Table 7. Best result (the average of 30 runs) obtained for the case study with 40 thermal units using FLC-DE.

Power	Generation (MW)	Power	Generation (MW)
P_1	110.8229	P_{21}	523.2726
P_2	110.7911	P_{22}	523.3006
P_3	97.3730	P_{23}	523.3567
P_4	179.7384	P_{24}	523.3277
P_5	88.0609	P_{25}	523.2831
P_6	139.9641	P_{26}	523.2844
P_7	259.6700	P_{27}	10.0210
P_8	284.6074	P_{28}	10.0838
P_9	284.5659	P_{29}	10.0856
P_{10}	130.0306	P_{30}	88.1420
P_{11}	168.7791	P_{31}	189.9875
P_{12}	168.7166	P_{32}	189.9684
P_{13}	214.7636	P_{33}	189.9367
P_{14}	394.3296	P_{34}	164.8195
P_{15}	304.4897	P_{35}	164.8087
P_{16}	394.2867	P_{36}	189.6040
P_{17}	489.3937	P_{37}	89.2105
P_{18}	489.3430	P_{38}	109.9947
P_{19}	511.2729	P_{39}	109.9283
P_{20}	511.2508	P_{40}	511.3367
		$\sum_{i=1}^{40} P_i$	10500

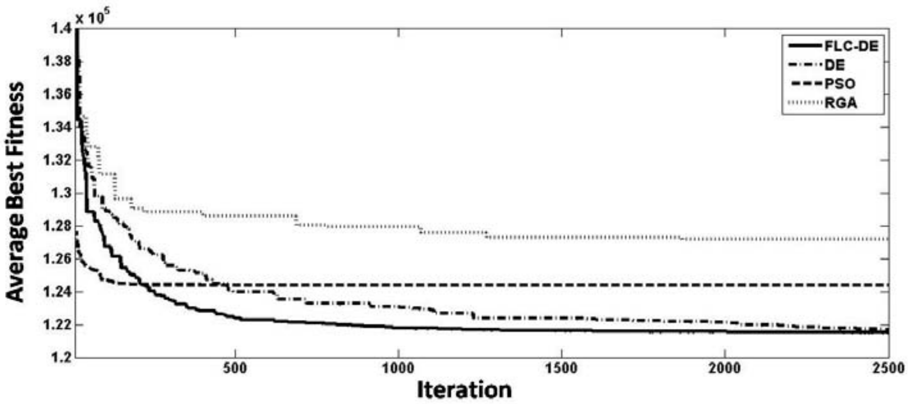

Figure 4. The progress of finding the average best solution by FLC-DE, DE, PSO and RGA over 30 independent runs for case study 2

6. Conclusion and further research

The ELD problem is a constrained optimization problem in power systems. An efficient method to solve this problem is using from EA algorithm. In this paper we used from a particular EA namely DE to solve ELD problem. We designed a fuzzy logic controller (FLC) to control the amplification factor vector of DE dynamically during the process of optimization. The proposed method (FLC-DE) obtained better results compared with the results obtained using DE with fixed set of offline-tuned parameters and results of PSO and RGA. In this work, we designed and tuned the FLC according to our experience and our understanding about the DE. We could get better results by using an FLC that tuned by means of a Global search techniques, such as a high-level EA.

7. Reference

[1] Abido, M.A.: Multi objective Evolutionary Algorithms for Electric Power Dispatch Problem, IEEE transactions on evolutionary computation, vol. 10, no. 3, pp.315--329 (2006).

[2] Wang, Y., Li, B., Weise, T.: Estimation of distribution and differential evolution cooperation for large scale economic load dispatch optimization of power systems, Information Sciences 180, pp. 2405--2420 (2010).

[3] Lee, F.N., Breipohl, A.M.: Reserve constrained economic dispatch with prohibited operating zones, IEEE Trans. Power Syst., pp.246--254 (1993).

[4] Bakirtzis, A., Petridis, V., Kazarlis, S.: Genetic algorithm solution to the economic dispatch problem, Generation, Transmission and Distribution, IEE Proceedings, pp. 377--382 (1994).

[5] Sheble, G.B., Brittig, K.: Refined genetic algorithm-economic dispatch example, IEEE Transactions on Power Systems, vol. 10 , pp. 117--124 (1994).

[6] Walters, D.C., Sheble, G.B.: Genetic algorithm solution of economic dispatch with valve point loading, IEEE Trans. on Power Systems, pp.1325--1332 (1993).

[7] Ma, H., El-Keib, A.A., Smith, R.E.: A genetic algorithm-based approach to economic dispatch of power systems, Southeastcon 94. Creative Technology Transfer - A Global Affair., Proceedings of the 1994 IEEE, pp. 212--216 (1994).

[8] Chen, P.H., Chang, H.C.: Large scale economic dispatch by genetic algorithm, IEEE Transactions on Power Systems, pp. 1919--1926 (1995).

[9] Yalcionoz, T., Altun, H., Uzam, M.: Economic dispatch solution using a genetic algorithm based on arithmetic crossover, Power Tech Proceedings, 2001 IEEE Porto, Vol. 2, pp. 4 (2001).

[10] Fung, C.C., Chow, S.Y., Wong, K.P.: Solving the economic dispatch problem with an integrated parallel genetic algorithm, Proc. PowerCon Int. Conf., vol. 3, pp. 1257--1262 (2000).

[11] Chiang, C.L.: Improved genetic algorithm for power economic dispatch of units with valve-point effects and multiple fuels, IEEE Transactions on Power Systems, pp.1690--1699 (2005).

[12] Gaing, Z.-L.: Particle swarm optimization to solving the economic dispatch considering the generator constraints, IEEE Trans. on Power Systems, pp.1187--1195 (2003).

[13] Park, J.B., Lee, K.S., Shin, J.R., Lee, K.Y.: A Particle Swarm optimization for economic dispatch with non-smooth cost functions, IEEE Transactions on Power Systems, pp.34--42 (2005).

[14] Eberhart, R.C., Shi, Y.: Comparison between genetic algorithms and particle swarm optimization, Proc. IEEE Int. Conf. Evol. Comput., pp. 611--616 (1998).

[15] Chaturvedi, K.T., Pandit, M., Srivastava, L.: Self-organizing hierarchical particle swarm optimization for nonconvex economic dispatch, IEEE Transactions on Power Systems, pp.1079--1087 (2008).

[16] Kumar, A., Dhanushkodi, K., Kumar, J., Paul, C.: Particle swarm optimization solution to emission and economic dispatch problem, Proc. Conf. Convergent Technologies for Asia–Pacific Region (TENCON-2003), vol. 1, pp. 435--439 (2003).

[17] El-Gallad, A., El-Hawary, M., Sallam, A., Kalas, A.: Particle swarm optimizer for constrained economic dispatch with prohibited operating zones, Proc. 2002 IEEE Canadian Conf. Elect. Comput. Eng., vol. 1, pp. 78--81 (2002).

[18] Gaing, Z.: Particle swarm optimization to solving the economic dispatch considering the generator constraints, IEEE Transactions on Power Systems, Vol. 18, pp. 1187--1195 (2003).

[19] Valle, V.D., Venayagamoorthy, G.K., Mohagheghi, S., Hernandez, J.C., Harley, R.G.: Particle swarm optimization: basic concepts, variants and applications in power systems, IEEE Transactions on Evolutionary Computation, Vol. 12, pp. 171--195 (2008).

[20] Zhao, B., Guo, C., Cao, Y.: Dynamic economic dispatch in electricity market using particle swarm optimization algorithm, Fifth World Congress on Intelligent Control and Automation, Vol. 6, pp. 5050--5054 (2004).

[21] Feoktistov, V.: Differential Evolution: In Search of Solutions, New York, Springer (2006).

[22] Liu, J., Lampinen, J.: A Fuzzy Adaptive Differential Evolution Algorithm, Soft Computing - A Fusion of Foundations, Methodologies and Applications, pp.448--462 (2005).

[23] Price, K.V., Storn, R.M., Lampinen, J.A.: Differential Evolution, A Practical Approach to Global Optimization, Heidelberg, Springer (2005).

[24] Storn, R.M., Price, K.V.: Differential Evolution – A Simple and Efficient Heuristic for Global Optimization over Continuous Spaces, Journal of Global Optimization, pp.341--359 (1997)

[25] Noman, N., Iba, H.: Differential evolution for economic load dispatch problems, Electric Power Systems Research, pp.1322--1331 (2008).
[26] Coelho, L.D.S., Souza, R.C.T., Mariani, V.C.: Improved differential evolution approach based on cultural algorithm and diversity measure applied to solve economic load dispatch problems, Mathematics and Computers in Simulation 79, pp. 3136--3147 (2009).
[27] Biswas, A., Dasgupta, S., Panigrahi, B.K., Pandi, V. R., Das, S., Abraham, A., Badr, Y.: Economic Load Dispatch Using a Chemotactic Differential Evolution Algorithm, HAIS, vol. 5572, pp. 252--260, Springer (2009).
[28] Kirchamayer, L.K.: Economic Operation of Power Systems , New York, Wiley, (1958).
[29] Hanzo, L.: Optimization Of Power System Operation, Canada, John Wiley & Sons (2009).
[30] Coelho, L.S., Mariani, V.C.: Combining of Chaotic differential evolution and quadratic programming for economic dispatch optimization with valve-point effect, IEEE Transactions on Power Systems, vol. 21, pp. 989 -- 996 (2006).
[31] Haupt, R.L., Haupt, E.: Practical Genetic Algorithms, second ed., Canada, John Wiley & Sons (2004).
[32] Wong, K.P., Wong, Y.W.: Genetic and genetic/simulated-annealing approaches to economic dispatch, IEE Proceedings – Control, Generation Transmission and Distribution, pp.507--513 (1994).