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Soft Computing Technique Based Economic Load Dispatch Using Improved Particle Swarm Optimization

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Abstract

This paper proposes a novel optimization methodology aimed to solve economic load dispatch (ELD) problem considering valve-point effects using improved particle swarm optimization (IPSO) algorithm through the application of Gaussian and Cauchy probability distributions. The IPSO approach introduces new diversification and intensification strategy into the particles thus preventing PSO algorithm from premature convergence. To demonstrate the effectiveness of the proposed approach, the numerical studies have been performed for two different test systems, i.e. 15 and 40 generating units, respectively. The obtained results denote superiority of the proposed technique and confirm its potential to solve the ELD problems.

Keywords: *Improved particle swarm optimization, economic load dispatch, valve-point effects.*

1. Introduction

The increasing energy demand and decreasing energy resources have necessitated the optimum use of available energy resources. The ELD problem is one of the fundamental issues in power system planning, operation, and control, where the total required load demand is distributed among the generation units in operation. The main goal of ELD problem of electrical power generation is to minimizing total generation cost while satisfying load demand and operational constraints. Traditionally, fuel cost function of a generator is represented by single quadratic function. But a quadratic function is not able to show the practical behavior of generator. The ELD problem is a non-convex and nonlinear optimization problem. Due to ELD complex and nonlinear characteristics, it is hard to solve the problem using classical optimization methods.

Most of classical optimization techniques such as lambda iteration method, gradient method, linear programming, Newton’s method, interior point method and dynamic programming have been used to solve the basic economic dispatch problem [1]. In the case of ELD is practically represented as a non-convex optimization problem with equality and inequalities constraints, which cannot be solved by traditional mathematical methods. Dynamic programming (DP) technique [2] can solve such types of problems, but it suffers from so-called the curse of dimensionality. Over the past few decades, as an alternative solution to the conventional mathematical approaches, many heuristic techniques have been developed for solving the ELD problem such as genetic algorithm (GA) [3], tabu search (TS) [4], simulated annealing (SA) [5], bacterial foraging optimization (BFO) [6], evolutionary programming (EP) [7], ant colony optimization (ACO) [8], harmony search [9], biogeography-based optimization (BBO) [10], particle swarm optimization (PSO) [11]-[14], differential evolution (DE) [15], and gravitational search algorithm (GSA) [16, 17].

Recently, a heuristic technique called as particle swarm optimization (PSO) is inspired the analogy of swarm of bird and school of fish were developed by Kennedy and Eberhart [18]. In PSO, each individual makes its decision based on its own experience together with other individual’s experiences. The individual particles are pulled stochastically toward the current individual velocity positions, their own best previous performance, and previous best performance from their neighbors [19].

In this paper, a novel approach is proposed to solve non-smooth ELD problems considering valve-point effects and transmission loss using an improved particle swarm optimization (IPSO) technique. Taking into account the Gaussian and Cauchy probability distributions into the

PSO algorithm is a useful strategy to ensure convergence of the particle swarm algorithm. Feasibility of the proposed method has been demonstrated on two different test systems, i.e. 15 and 40 generating units. The results obtained with the proposed technique were compared with other optimization results reported in literature.

2. Problem Formulation

The purpose of the ELD problem is to find the optimal scheduling of power generations that minimizes the total generation cost while satisfying equality and inequality constraints. The fuel cost curve for any unit is assumed to be approximated by segments of quadratic functions of the active power output of the generator. For a given power system network, the problem may be described as optimization (minimization) of total fuel cost under a set of operating constraints.

$$F_T = \sum_{i=1}^{n} F_i(P_i) = \sum_{i=1}^{n} \left(a_i P_i^2 + b_i P_i + c_i\right) \qquad (1)$$

where F_T is total fuel cost of generation in the system (\$/h), a_i, b_i, and c_i are the cost coefficient of the *i*th generator, P_i is the power generated by the *i*th unit and n is the number of generators. The cost is minimized subjected to the following constraints:

2.1 Active Power Balance Equation

The total generated power by the units must be the same as total load demand plus the total transmission loss.

$$P_D = \sum_{i=1}^{n} P_i - P_{Loss} \qquad (2)$$

where P_D and P_{Loss} are the total load demand and total transmission losses, respectively. The transmission loss can be calculated by using ***B*** matrix technique and is defined as follows:

$$P_{Loss} = \sum_{i=1}^{n}\sum_{j=1}^{n} P_i B_{ij} P_j + \sum_{i=1}^{n} B_{0i} P_i + B_{00} \qquad (3)$$

where B_{ij} is coefficient of transmission losses and the B_{0i} and B_{00} is matrix for loss in transmission which are constant under certain assumed conditions.

2.2 Minimum and Maximum Power Limits

The generation output of each units must be lie between minimum and maximum limits. The corresponding inequality constraint for each generator is

$$P_{i,\min} \le P_i \le P_{i,\max} \text{ for } i = 1,2,\cdots,n \qquad (4)$$

where $P_{i,min}$ and $P_{i,max}$ are the minimum and maximum outputs of the *i*th generator, respectively.

2.3 Valve-Point Effects

For more rational and precise modeling of fuel cost function, the above expression of cost function is to be modified suitably. The generating units with multi-valve steam turbines exhibit a greater variation in the fuel-cost functions [12]. These “valve-point effects” are illustrated in Fig. 1.

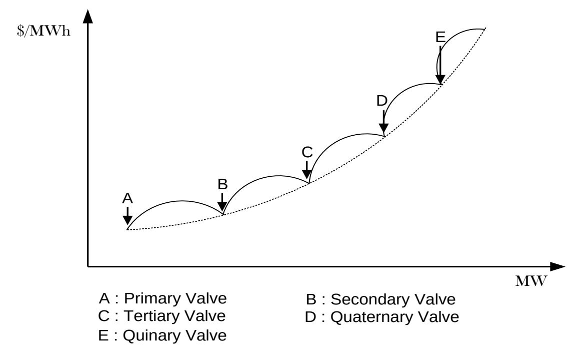

Fig. 1 Valve-point effect [12]

The fuel cost function with valve-point effects of the generators is usually modeled as [12]:

$$F_T = \sum_{i=1}^{n} F_i(P_i) = \sum_{i=1}^{n} \left(\begin{array}{l} a_i P_i^2 + b_i P_i + c_i + \\ \left| e_i \times \sin\left(f_i \times \left(P_{i,\min} - P_i\right)\right)\right| \end{array} \right) \qquad (5)$$

where F_T is total fuel cost of generation in (\$/h) including valve point loading, e_i, f_i are fuel cost coefficients of the *i*th generating unit reflecting valve-point effects.

3. Particle Swarm Optimization

3.1 Overview of Particle Swarm Optimization

The PSO method was introduced in 1995 by Kennedy and Eberhart [18]. The method is motivated by social behavior of organisms such as fish schooling and bird flocking. PSO provides a population-based search procedure in which individuals called particles change their position with time. In a PSO system, particles fly around in a multi dimensional search space. During the evolutionary process, each particle adjust its position based on its own experience as well as the experience of the neighboring particles, making use of the best position encountered by itself and its neighbors.

The velocity of a particle is influenced by three components, namely: inertial, cognitive and social [19]. The inertial component simulates the inertial behavior of

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the bird to fly in the previous direction. The cognitive component models the memory of the bird about its previous best position, and the social component models the memory of the bird about the best position among the particles. The particles move around the multidimensional search space until they find the optimal solution. The modified velocity of each agent can be calculated using the current velocity and the distance from *Pbest* and *Gbest* as given below.

$$V_i^{k+1} = W \times V_i^k + C_1 \times r_1 \times \left(Pbest_i^k - X_i^k\right) + C_2 \times r_2 \times \left(Gbest^k - X_i^k\right) \quad (6)$$

where,

V_i^k	velocity of individual *i* at iteration *k*
X_i^k	position of individual *i* at iteration *k*
W	inertia weight
C_1, C_2	acceleration coefficients
$Pbest_i^k$	best position of individual *i* at iteration *k*
$Gbest^k$	best position of the group until iteration *k*
r_1, r_2	random numbers between 0 and 1

In general, the inertia weight (*W*) is set according to the following equation [12]:

$$W = W_{\max} - \left(\frac{(W_{\max} - W_{\min})}{Iter_{\max}}\right) \times Iter \quad (7)$$

where,

$W_{\max}, W_{\min}$	initial and final weights
$Iter_{\max}$	maximum iteration number
$Iter$	current iteration number

The approach using (7) is called "inertia weight approach (IWA)". By using (7), a certain velocity, which gradually gets close to *Pbest* and *Gbest* can be calculated. The current position (searching point in the solution space), each individual move from the current position to the next one by the modified velocity in (6) using the following equation:

$$X_i^{k+1} = X_i^k + V_i^{k+1} \quad (8)$$

where,

X_i^{k+1}	current position of individual *i* at iteration *k*+1
V_i^{k+1}	velocity of individual *i* at iteration *k*+1

The concept of the searching mechanism of PSO using the modified velocity and position of individual *i* based on (6) and (8) if the value of *W*, C_1, C_2, r_1, and r_2 are 1, as shown in Fig. 2.

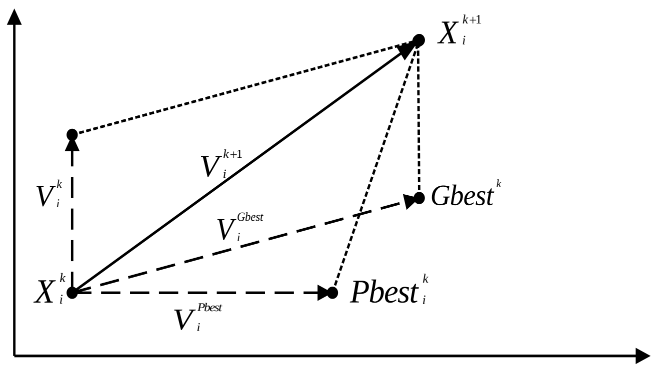

Fig. 2 Concept of modification of searching point by PSO [18]

The process of implementing the PSO is as follows:

Step 1: Create an initial population of individual with random positions and velocity within the solution space.
Step 2: For each individual, calculate the value of the fitness function.
Step 3: Compare the fitness of each individual with each *Pbest*. If the current solution is better than its *Pbest*, then replace its *Pbest* by the current solution.
Step 4: Compare the fitness of all individual with *Gbest*. If the fitness of any individual is better than *Gbest*, then replace *Gbest*.
Step 5: Update the velocity and position of all individual according to (6) and (8).
Step 6: Repeat steps 2-5 until a criterion is met.

3.2 Improved Particle Swarm Optimization

In recent research, some modifications to the standard PSO are proposed mainly to improve the convergence and to increase diversity. Coelho and Krohling [20] proposed the use of truncated Gaussian and Cauchy probability distribution to generate random numbers for the velocity updating equation of PSO. The proposed IPSO technique is based on Gaussian probability distribution (*Gd*) and Cauchy probability distribution (*Cd*). In this new approach, random numbers are generated using Gaussian probability function and/or Cauchy probability function in the interval [0, 1].

The Gaussian distribution (*Gd*), also called normal distribution is an important family of continuous probability distributions. Each member of the family may be defined by two parameters, location and scale: the mean and the variance respectively. A standard normal distribution has zero mean and variance of one. Hence importance of the Gaussian distribution is due in part to the central limit theorem. Since a standard Gaussian distribution has zero mean and variance of value one, it helps in a faster convergence for local search.

Here the Cauchy distribution *Cd*, is used to generate random numbers in the interval [0, 1], in the social part and Gaussian distribution *Gd*, is used to generate random numbers in the interval [0, 1] in the cognitive part. The modified velocity equation (6) is given by

$$V_i^{k+1} = K \cdot \begin{pmatrix} W.V_i^k + C_1 G_d()(Pbest_i^k - X_i^k) \\ + C_2 C_d()(Gbest^k - X_i^k) \end{pmatrix} \quad (9)$$

$$K = \frac{2}{\left|2 - \varphi - \sqrt{\varphi^2 - 4\varphi}\right|} \quad (10)$$

where $\varphi = C_1 + C_2,\ \varphi > 4$

The convergence characteristic of the system can be controlled by φ . In the constriction factor approach (CFA), φ must be greater than 4.0 to guarantee stability. However, as φ increases, the constriction factor K decreases and diversification is reduced, yielding slower response. Typically, when the constriction factor is used, φ is set to 4.1 (i.e. C_1, C_2 = 2.05) and the constant multiplier K is thus 0.729.

4. Simulation Results

In order to demostrate the efficiency of the proposed technique, two different power systems were tested: (1) 15-unit system considering transmission loss and valve-point effects; and (2) 40-unit system with valve-point effects and transmission losses are neglected.

Test Case 1: 15-unit system

This system consists of 15 generating units and the input data of 15-generator system are given in Table 1 [11], [21]. Transmission loss B-coefficients are taken from [21]. In order to validate the proposed IPSO method, it is tested with 15-unit system having non-convex solution spaces, and the load demand is 2630 MW.

The best fuel cost result obtained from proposed IPSO and other optimization algorithms are compared in Table 2 for load demands of 2630 MW. In Table 2, generation outputs and corresponding fuel cost and losses obtained by the proposed IPSO are compared with those of GA and PSO [21]. The proposed IPSO provides better solution (total generation cost of 30320.7233 $/h and power loss of 30.4039 MW) than other methods while satisfying the system constraints. We have also observed that the solutions by IPSO always are satisfied with the equality and inequality constraints.

Test Case 2: 40-unit system

This system consisting of 40 generating units and the input data for 40-generator system is given in Table 3 [7]. The total demand is set to 10500 MW.

The obtained results for the 40-unit system using the proposed IPSO technique are given in Table 4 and the results are compared with other methods reported in literature, including PSO, PPSO, APPSO and GSA [17, 22]. It can be observed that the proposed technique can get total generation cost of 121031.1225 $/h, which is the best solution among all the methods. These results show that the proposed methods are feasible and indeed capable of acquiring better solution.

Table 1: Generating unit capacity and coefficients (15-units)

Unit	$P_{i,min}$	$P_{i,max}$	a_i	b_i	c_i	e_i	f_i
1	150	455	0.000299	10.1	671	100	0.084
2	150	455	0.000183	10.2	574	100	0.084
3	20	130	0.001126	8.8	374	100	0.084
4	20	130	0.001126	8.8	374	150	0.063
5	150	470	0.000205	10.4	461	120	0.077
6	135	460	0.000301	10.1	630	100	0.084
7	135	465	0.000364	9.8	548	200	0.042
8	60	300	0.000338	11.2	227	200	0.042
9	25	162	0.000807	11.2	173	200	0.042
10	25	160	0.001203	10.7	175	200	0.042
11	20	80	0.003586	10.2	186	200	0.042
12	20	80	0.005513	9.9	230	200	0.042
13	25	85	0.000371	13.1	225	300	0.035
14	15	55	0.001929	12.1	309	300	0.035
15	15	55	0.004447	12.4	323	300	0.035

Table 2: Best solution of 15-unit systems

Unit power output	GA [21]	PSO [21]	IPSO
P1 (MW)	415.3108	439.1162	455.0000
P2 (MW)	359.7206	407.9729	363.1539
P3 (MW)	104.4250	119.6324	71.3987
P4 (MW)	74.9853	129.9925	75.1350
P5 (MW)	380.2844	151.0681	364.5806
P6 (MW)	426.7902	459.9978	408.7329
P7 (MW)	341.3164	425.5601	403.8775
P8 (MW)	124.7876	98.5699	108.0356
P9 (MW)	133.1445	113.4936	66.1967
P10 (MW)	89.2567	101.1142	133.1241
P11 (MW)	60.0572	33.9116	53.7672
P12 (MW)	49.9998	79.9583	40.5174
P13 (MW)	38.7713	25.0042	39.7611
P14 (MW)	41.4140	41.4140	54.6636
P15 (MW)	22.6445	36.6140	22.4498
Total power output (MW)	2668.2782	2662.4306	2660.4039
Total generation cost ($/h)	33113.0	32858.0	30320.7233
Power loss (MW)	38.2782	32.4306	30.4039

Table 3: Generating unit capacity and coefficients (40-units)

Unit	$P_{i,min}$	$P_{i,max}$	a_i	b_i	c_i	e_i	f_i
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	287.71	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	12.9	722.82	200	0.042
11	94	375	0.00515	12.9	635.20	200	0.042
12	94	375	0.00569	12.8	654.69	200	0.042
13	125	500	0.00421	12.5	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	8.62	116.58	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 4: Best solution of 40-unit systems

Unit power output	PSO [22]	PPSO [22]	APPSO [22]	GSA [17]	IPSO
P1 (MW)	113.116	111.601	112.579	110.2604	112.6115
P2 (MW)	113.010	111.781	111.553	105.8822	112.8864
P3 (MW)	119.702	118.613	98.751	96.5985	119.1771
P4 (MW)	81.647	179.819	180.384	161.3755	131.8259
P5 (MW)	95.062	92.443	94.389	76.0761	97.0000
P6 (MW)	139.209	139.846	139.943	118.3619	138.7205
P7 (MW)	299.127	296.703	298.937	277.7329	190.0615
P8 (MW)	287.491	284.566	285.827	282.9290	254.9897
P9 (MW)	292.316	285.164	298.381	255.8505	287.9621
P10 (MW)	279.273	203.859	130.212	198.4792	130.4386
P11 (MW)	169.766	94.283	94.385	194.7330	370.7440
P12 (MW)	94.344	94.090	169.583	261.4072	373.1686
P13 (MW)	214.871	304.830	214.617	302.8148	445.7441
P14 (MW)	304.790	304.173	304.886	363.7843	336.5109
P15 (MW)	304.563	304.467	304.547	325.7610	358.3672
P16 (MW)	304.302	304.177	304.584	382.4561	408.1342
P17 (MW)	489.173	489.544	498.452	470.1274	287.8605
P18 (MW)	491.336	489.773	497.472	451.5342	458.1819
P19 (MW)	510.880	511.280	512.816	478.0455	375.9790
P20 (MW)	511.474	510.904	548.992	500.7619	442.5035
P21 (MW)	524.814	524.092	524.652	529.9021	506.2721
P22 (MW)	524.775	523.121	523.399	515.3287	548.1050
P23 (MW)	525.563	523.242	548.895	529.2006	445.3442
P24(MW)	522.712	524.260	525.871	518.1049	538.5089
P25 (MW)	503.211	523.283	523.814	489.4889	387.6950
P26 (MW)	524.199	523.074	523.565	513.8339	484.9672
P27 (MW)	10.082	10.800	10.575	10.6119	48.6070
P28 (MW)	10.663	10.742	11.177	10.2303	61.0371
P29 (MW)	10.418	10.799	11.210	12.8966	74.8758
P30 (MW)	94.244	94.475	96.178	92.6348	96.6173
P31(MW)	189.377	189.245	189.999	187.9979	189.0000
P32 (MW)	189.796	189.995	189.924	176.9925	189.6533
P33 (MW)	189.813	188.081	189.714	184.4834	182.1303
P34 (MW)	199.797	198.475	199.284	146.4241	121.3866
P35 (MW)	199.284	197.528	199.599	172.6954	198.5367
P36 (MW)	198.165	196.971	199.751	183.6914	124.0439
P37 (MW)	109.291	109.161	109.973	101.0808	109.2031
P38 (MW)	109.087	109.900	109.506	104.7847	109.1819
P39 (MW)	109.909	109.855	109.363	90.2306	109.2571
P40 (MW)	512.348	510.984	511.261	514.4148	542.7402
Total generation cost ($/h)	122323.97	121788.22	122044.63	121940.0	121031.1225

5. Conclusions

This paper presents a new approach for solving the non-smooth ELD problem using an improved particle swarm optimization (IPSO) technique. The proposed technique has provided the global solution in the 15-unit and 40-unit test systems and the better solution than the previous studies reported in literature. The non-linear characteristics such as valve-point effects, equality and inequality constraints have been considered for practical generation operation in power systems. The application of Gaussian and Cauchy probability distributions in proposed approach is a powerful strategy to improve the global searching capability and escape from local minima. Also, the equality and inequality constraints treatment methods have always provided the solutions satisfying the constraints.

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