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Static Economic LoadDispatch of Generators Including Transmission Losses using Differential Evolution

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Abstract: Economic Dispatch is the process of allocating the required load demand between the available generation units such that the cost of operation is minimized. There have been many algorithms proposed for economic dispatch out of which a Differential Evolution (DE) is discussed in this paper. Differential Evolution (DE) is very effective for solving optimization problems with non-smooth and non-convex characteristics. This technique combines simple arithmetic operator with classic evolutionary operators, such as mutation, crossover and selection. The key idea behind DE is a scheme for generating trial vectors. Mutation is used to generate a mutant vector by adding differential vectors obtained from the difference of several randomly chosen parameter vectors to the parent vector. After that, a trial vector is produced by a crossover through recombining the obtained mutant vector with the target vector. The DE is used to solve the Economic Dispatch problem (ED) with transmission loss by satisfying the linear equality and inequality constraints. The proposed method is compared with Lemda Iteration(LI),Genetic Algorithm (GA),Artificial Bee Colony(ABC), Particle Swarm Optimization (PSO) for a 3 Unit Test System and 6 UNIT Test System.

Keywords: Differential Evolution, Genetic Algorithm, Artificial Bee Colony, Particle Swam Optimisation.

I INTRODUCTION

In real world, as competition increases in the power generationindustry, generating companies try to further improve the operating efficiency oftheir power plants. The application of mathematical optimization techniques has a long history in power generation systems and tangible improvements can still beachieved through the application of more robust solution techniques. Economicdispatch (ED) is one of the major important optimization task in power generations systems. The objective of economic dispatch is to find the optimal combination of power dispatches from different power generating units in a given time period to minimise total generating cost while satisfying the load demand and generating units operating conditions[1].

In the traditional ED problem, the cost function for each generator has been approximately represented by a single quadratic function and is solved using mathematical programming based optimization techniques such as lambda iteration method, gradient-based method[2]. These methods require incremental fuel cost curves which are piecewise linear and monotonically increasing to find the global optimal solution. This makes the problem of finding the global optimum solution challenging. Dynamic programming (DP) method[3] is one of the approaches to solve the non-linear and discontinuous ED problem, but it suffers from the problem of “curse of dimensionality” or local optimality. In order to overcome this problem, several alternative methods have been developed such as Geneticalgorithm (GA) Particle swarm optimization (PSO) ArtificialBeeColony(ABC) and DifferentialEvolution(DE) A genetic algorithm (GA) [4] is a search heuristic that mimics the process of natural evolution. Genetic algorithms belong to the larger class of evolutionary algorithms (EA). The GA procedure is based on the principle of survival of the fittest. The algorithm identifies the individuals with the optimizing fitness values, and those with lower fitness will naturally get discarded from the population. But there is no absolute assurance that a genetic algorithm will find a global optimum. Also the genetic algorithm cannot assure constant optimization response times. These unfortunate genetic algorithm properties limit the genetic algorithms use in optimization problems.

Particle Swarm Optimization (PSO) [7] is motivated by social behaviour of organisms such as bird flocking and fish schooling. The PSO is an optimization tool, which provides a population-based search procedure. A PSO system combines local search methods with global search methods, but no guaranteed convergence even to local minimum. It has the problems of dependency on initial point and parameters, difficulty in finding their optimal design parameters, and the stochastic characteristic of the final outputs.

Differential evolution algorithm [13,14] is a simple and powerful population-based stochastic optimization algorithm, which is originally motivated by the mechanisms of natural selection. Since it does not require the derivative information, DE is very effective for solving optimization problem with non-smooth and non-convex characteristics. This technique combines simple arithmetic operator with classic evolutionary operators, such as mutation, crossover and selection. The key idea behind DE is a scheme for generating trial vectors. Mutation is used

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to generate a mutant vector by adding differential vectors obtained from the difference of several randomly chosen parameter vectors to the parent vector. The crossover operator generates the trial vector by combining the parameters of the mutant vector with the parameters of a parent vector selected from the population. In the selection operator the trial vector competes against the parent vector and the one with better performance advances to the next generation. This process is repeated over several generations resulting in an evolution of the population to an optimal value. In this paper, Differential Evolution is discussed to solve the ED problem by considering the linear equality and inequality constraints for a three units and IEEE 30BUSsixunits system and the results were compared with GA, PSO and ABC. The algorithm described in this paper is capable of obtaining optimal solutions efficiently.

II NOMECULATURE

F_T Fuel cost of the system
F_i Fuel cost of the generating unit of the system i
P_{Gi} Power generated in the generating unit
N Number of generators
a_i,b_i,c_i Cost coefficients of the i_{th} generator
P_D Power demand
P_L Transmission losses
P_{Gi}^{min} Minimum value of the real power
P_{Gi}^{max} Maximum value of the real power
X_j^{min} Lower bound of initial population for j_{th} component
X_j^{max} Upper bound of initial population for j_{th} component
N_P Number of individuals in population P
Rand[0,1] Uniform random number in the interval [0,1]
D Dimension
P Initial population
P_{add} Additional population to create new population for IDE
P_{new} New population for IDE
X_{ra},X_{rb} Random individuals for mutation
And X_{rc}
F Scaling factor for mutation
C_r Crossover constant
f(x) Fitness function

III. ECONOMIC LOAD DISPATCH PROBLEM

The principal objective of the economic load dispatch problem is to find a set of active power delivered by the committed generators to satisfy the required demand subject to the unit technical limits at the lowest production cost. The optimization of the ELD problem is formulated in terms of the fuel cost expressed as,

$$F_T=\sum_{i=1}^{N} F_i(P_{Gi})=\sum_{i=1}^{N} a_i+b_iP_{Gi}+c_iP_{Gi}^2 \qquad (1)$$

Constraint 1: Generation capacity constraint
For normal system operations, real power output of each generator is restricted by lower and upper bounds as follows:

$$P_{Gi}^{min} \le P_{Gi} \le P_{Gi}^{max} \qquad (2)$$

Constraint 2: Power balance constraint

The total power generation must cover the total demand $P_D$and the real power loss in transmission lines P_L. This relation can be expressed as:

$$P_{Gi} = P_D + P_L \qquad (3)$$

Here a reduction is applied to model transmission losses as a function of the generators output through Kron's loss coefficients. The Kron's loss formula can be expressed as follows:

$$P_L=\sum_{i=1}^{N}\sum_{j=i}^{N} P_{Gi}B_{ij}P_{Gj}+\sum_{i=1}^{N} B_{0i}\, P_{Gi}+B_{00} \qquad (4)$$

where B_{ij}, B_{0i}, $B_{00}$are the transmission network power loss B-coefficients, which are assumed to be constant, and reasonable accuracy can be achieved when the actual operating conditions are close to the base case where the B-coefficients were derived. In the summary, the objective of economic power dispatch optimization is to minimize $F_T$subject to the constraints (2) and (3).

IV. PROPOSED DIFFERENTIALEVOLUTION

Differential Evolution is one of the most recent population based stochastic evolutionary optimization techniques. Storn and Price first proposed DE in 1995 [13, 14] as a heuristic method for minimizing non-linear and non-differentiable continuous space functions. Differential Evolution includes Evolution Strategies (ES) and conventional Genetic Algorithms (GA). Differential Evolution is a population based search algorithm, which is an improved version of Genetic Algorithm. One extremely powerful algorithm from Evolutionary Computation due to convergence characteristics and few control parameters is differential evolution. Like other evolutionary algorithms, the first generation is initialized randomly and further generations evolve through the application of certain evolutionary operator until a stopping criterion is reached. The optimization process in DE is carried with four basic operations namely, Initialization, Mutation, Crossover and Selection.

A. Initialization

The first step in the DE optimization process is to create an initial population of candidate solutions by assigning random values to each decision parameter of each individual of the population. The initial population is chosen randomly in order to cover the entire searching region uniformly. A uniform probability distribution for All random variables is assumed as in the following equation

$$X_{ji}^0=X_j^{min} + rand()*(X_j^{max} - X_j^{min}) \quad i=1,2.....P \; j=1,2....N \qquad (5)$$

$X_{ji}^0$is the initialized j^{th} decision variable of i^{th}population set

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B. Mutation:

Mutation occupies quite an important role in the reproduction cycle. The mutation operation creates mutant vectors $X`_i^k$ by perturbing a randomly selected vector X_a^k with the difference of two other randomly selected vectors X_b^k and X_c^k at kth iteration as per following equation.

$$\boldsymbol{X`_i^k} = \boldsymbol{X_a^k} + \mathbf{F}*(\boldsymbol{X_b^k} + \boldsymbol{X_c^k}) \quad i = 1, 2......P \qquad (6)$$

where

$X`_i^k$ is the newly generated i[th] population set after performing mutation operation at k[th] iteration

X_a^k , X_b^k are randomly chosen vectors at k[th]

X_c^k iteration

The mutation factor F is a user chosen parameter used to control the perturbation size in the mutation operator and to avoid search stagnation.

C. Crossover

Crossover represents a typical case of a 'genes' exchange. The crossover operation maintains diversity in the population, preventing local minima convergence.The crossover constant (CR) must be in the range of [0, 1]. A crossover constant of one means the trial vector will be composed entirely of mutant vector parameters. A crossover constant near zero results in more probability of having parameters from target vector in trial vector. A randomly chosen parameter from mutant vector is always selected to ensure that the trial vector gets at least one parameter from mutant vector even if the crossover constant is zero.The parent vector is mixed with the mutated vector to create a trial vector, according to the following equation;

$$\boldsymbol{X``_{ji}^k} = \boldsymbol{X`_{ji}^k} if randj \leq CR or j = q \quad \boldsymbol{X``_{ji}^k}$$

otherwise i=1,2........P j=1,2.......N (7)

where

X_{ji}^k is the j[th] individual ofi[th] target vector at k[th] iteration

$X`_{ji}^k$ is the j[th] individual of i[th] mutant vector at k[th] iteration;

$X``_{ji}^k$ is the j[th] individual ofi[th] trial vector at k[th] iteration;

qis a randomly chosen index

D. Selection

Selection is the operation through which better offspring are generated. The evaluation (fitness) function of an offspring is compared to that of its parent. The parent is replaced by its offspring if the fitness of the offspring is better than that of its parent, while the parent is retained in the next generation if the fitness of the offspring is worse than that of its parent. The selection operator chooses the vector that is going to compose the population in the next generation. The selection is repeated for each pair of targettrial vector until the population for the next generation is complete. Thus, if f denotes the cost (fitness) function under optimization (minimization), then

$$\boldsymbol{X_i^{k+1}} = \boldsymbol{X``_i^k} \text{ if } f(\boldsymbol{X``_i^k}) \leq f(\boldsymbol{X_i^k}) \ \boldsymbol{X_i^k} \ i=1,2.....P \qquad (8)$$

where

X_i^{k+1} is the i[th] population set obtained after selection operation at the end of k[th] iteration, to be used as parent population set in next iteration (k + 1)[th].

The optimization process is repeated for several generations. This allows individuals to improve their fitness while exploring the solution space for optimal values. The iterative process of mutation, crossover and selection on the population will continue until a user-specified stopping criterion, normally, the maximum number of generations allowed, is met. The other type of stopping criterion, i.e. convergence to the global optimum is possible if the global optimum of the problem is available

V. CASE STUDIES

The efficiency of the proposed algorithm for solving Economic Load Dispatch (ELD) problem has been tested on two different power generating units – the 3 unit and 6 unit system including the transmission losses. The performances of these algorithms are evaluated and compared with classical Lambda Iteration Method (LIM) and other meta-heuristics available in literature. The algorithms are implemented in MATLAB R2009b platform on i5 processor, 2.53 GHz, 4 GB RAM personal computer.

A.TestSystem I: 3 UNIT SYSTEM

In order to demonstrate the effectiveness of the DE algorithm, the ELD benchmark consisting of three generator units [16] is selected. The detailsof fuel cost coefficients and generating limits foreach unit are given in Table I and hourly load distribution over 24 hour horizon is given in Table II respectively.The Transmission Loss Coefficient Matrix for calculating power loss of 3 Unit test system can beobtained from [16].The generalized DE parameters and their settings for the ELD problem are listed in Table III. For optimal parameters, simulations were carried out for 50 trials each time varying the basic parameters like scale factor (F), Crossover rate (Cr) and population size (P).

Table I
Generating unit's capacity and Coefficients

Unit	P_{Gi}^{min} (MW)	P_{Gi}^{max} (MW)	a_i ($)	b_i ($/MW)	c_i ($/MW^2)
1	100	220	176.9	13.5	0.1
2	10	100	129.9	32.6	0.1
3	10	20	137.4	17.6	0.1

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TableII Hourly Load

Hour	P_D(MW)	Hour	P_D(MW)
1	175.19	13	242.18
2	165.15	14	243.60
3	158.67	15	248.86
4	154.73	16	255.79
5	155.06	17	256
6	160.48	18	246.74
7	173.39	19	245.97
8	177.60	20	237.35
9	186.81	21	237.31
10	206.96	22	232.67
11	228.61	23	195.93
12	236.10	24	195.60

Table III
Parameters of DE used to implementeld for3unitsystem

Parameters of DE		**Notation Used**	**Values**
1.	No of members in population	P	[20 100]
2.	Vector of lower bounds for initial population	X_j^{min}	[-2, 2]
3.	Vector of upper bounds for initial population	X_j^{max}	[2 , 2]
4.	Number of iterations	Iter	200
5	Dimension	D	2
6.	Crossover Rate	Cr	[0,1]
7.	Step size F	F	[0,2]
8.	Strategy parameter	DE/best/2/bin	9
9.	Refresh parameter	R	10
10.	Value to Reach	VTR	1e-6

Transmission Loss Coefficient Matrix

$$B_{ij} = \begin{bmatrix} 0.00014 & 0.000017 & 0.000015 \\ 0.000017 & 0.000060 & 0.000013 \\ 0.000015 & 0.00003 & 0.000065 \end{bmatrix}$$

$$B_{00} = [0]$$

$$B_{0i} = [0\ 0\ 0]$$

Simulation results for test system I:

With the best values of P = 20, F = 0.8 and Cr = 0.5, the DE algorithm was run for different values of demand ranging for 24 hours. For each demand, 50independent trials with 200 iterations pertrial have been performed. The individual generator powers, minimum fuel cost, total power generated, power loss and the simulation results are shown in Table V.

Comparative Analysis:

The results of the proposed DE for 6bus 3unit system are compared with other reported approaches such as PSO, GA and ABC. The economic dispatch obtained through the LI method was also used for comparison and all the results are shown in Table VI. The minimum cost for the demand for 24hour horizon compared to all others, while the proposed DE produced a cost of$161708.02, promisingly optimal and consistent. The power loss during the optimal dispatch was 81.4528MWrelatively less than all other meta-heuristic algorithms

B. Test System II: 6UNIT SYSTEM

The six unit test system has beenadoptedfrom [17], in which the fuel costcoefficients, and power limits are known. Thespecifications of the system for six generator testsystem are detailed inTable IV and hourly load distribution over 24 hour horizon is given in Table VIIrespectively.The Transmission Loss Coefficient Matrix for calculating power loss of 6 Unit test system can beobtained from [17].The various DE parameters used to implement ELD problem for 6unit generating system is similar to that of the three unit test system except for the dimension which is varied based on the size of the problem. Here D=5 for 6 unit system and the population is usually setbased on 10 times the D value. Notations of the parameters and the range of values are given in TableIII

Table IV Generating unit's capacity and Coefficients

Unit	P_{Gi}^{min} (MW)	P_{Gi}^{max} (MW)	a_i ($)	b_i ($/MW)	c_i ($/MW^2)
1	100	500	240	7.00	0.0070
2	50	200	200	10.0	0.0095
3	80	300	220	8.5	0.0090
4	50	150	200	11.0	0.0090
5	50	200	220	10.50	0.0080
6	50	120	190	12.0	0.0075

Transmission Loss Coefficient Matrix

$$B_{0i} = 1e^{-04}[-3.908\ -1.297\ 7.047\ 0.591\ 2.161\ -6.635]$$

$$B_{00} = [0.056]$$

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$$B_{ij} = e^{-03} * \begin{bmatrix} 1.7 & 1.2 & 0.7 & -0.1 & -0.5 & -0.2 \\ 1.2 & 1.4 & 0.9 & 1.0 & -0.6 & -0.1 \\ 0.7 & 0.9 & 3.1 & 0 & -1.0 & -0.6 \\ -0.1 & 0.1 & 0 & 2.4 & -0.6 & -0.8 \\ -0.5 & -0.6 & -1.0 & -0.6 & 12.9 & -0.2 \\ -0.2 & -0.1 & -0.6 & -0.8 & -0.2 & 15.0 \end{bmatrix}$$

Simulation results for test system II:

With the best values of P = 50, F = 0.8 and Cr = 0.5 the DE algorithm was run for different values of demand ranging for 24 hours. For each demand, 50independent trials with 200 iterations pertrial have been performed. The individual generator powers, minimum fuel cost, total power generated, power loss and the simulation results are shown in Table VII.

Comparative Analysis :

The results of the proposed DE for 6unit system are compared with other reported approaches such as PSO, GA and ABC. The economic dispatch obtained through the LI method was also used for comparison and all the results are shown in Table VIII. The minimum cost for the demand for 24hour horizon compared to all others, while the proposed DE produced a cost of 319475.79$/hr, promisingly optimal and consistent. The power loss during the optimal dispatch was232.8340 MW relatively less than all other meta-heuristic algorithms

Table VSimulation results for 3 Unit Test System

P_D	P_L	P_{G1}	P_{G2}	P_{G3}	F_T
175.19	2.476	123.84	33.83	20	5258.82
165.15	2.254	118.85	28.54	20	4865.21
158.67	2.1176	115.64	25.14	20	4617.65
154.73	2.037	113.69	23.08	20	4469.12
155.06	2.0436	113.85	23.25	20	4481.49
160.48	2.1552	116.54	26.09	20	4686.45
173.39	2.4354	122.95	32.88	20	5187.52
177.60	2.5311	125.04	35.1	20	5354.85
186.81	2.748	129.61	39.95	20	5727.71
206.96	3.2587	139.61	50.61	20	6576.0
228.61	3.8629	150.37	62.11	20	7537.54
236.10	4.0854	154.09	66.09	20	7882.36
242.18	4.2711	157.11	69.34	20	8166.87
243.60	4.3151	157.82	70.09	20	8233.92
248.86	4.4803	160.44	72.9	20	8484.24
255.79	4.7033	163.88	76.61	20	8818.79
256	4.7101	163.99	76.72	20	8829.01
246.74	4.4133	159.38	71.77	20	8382.98
245.97	4.3891	159.0	71.36	20	8346.32
237.35	4.1232	154.71	66.76	20	7940.51
237.31	4.122	154.69	66.74	20	7938.65
232.67	3.9826	152.39	64.27	20	7723.67
195.93	2.973	134.13	44.77	20	6106.1
195.60	2.9647	133.97	44.60	20	6092.25

Total cost of Production=$161708.02
Total Power Loss = 81.4528MW

Table VI Comparison of results for 3 UNIT System

METHOD	TOTAL LOSS (MW)	TOTAL COST ($)
LI	121.6972	163472.92
GA	82.4528	161718.62
PSO	83.2822	161920.37
DE	81.4528	161708.02
ABC	82.1764	161715.5

Table VII Simulation results for 6 Unit Test System

Hour	P_D	P_L	F_T
1	1293	12.874	15850.65
2	1253	11.9944	15309.26
3	1240	11.9815	15132.06
4	1223	11.688	14903.54
5	1202	11.3556	14622.57
6	1190	11.1078	14462.5
7	1175	10.8599	14263.16
8	1160	10.6084	14064.51
9	1145	10.3454	13866.53
10	1130	10.0961	13669.26
11	1119	9.9222	13525.04
12	1102	9.6539	13302.88
13	1095	9.5449	13211.67
14	1080	9.3131	13016.72
15	1065	9.0855	12822.46
16	1050	8.8632	12628.89
17	1035	8.6361	12436.03
18	1020	8.4025	12243.97
19	1009	8.2339	12103.66
20	999	8.0823	11976.5
21	985	7.8731	11799.09
22	970	7.6527	11609.8
23	955	7.4359	11421.35
24	940	7.2236	11233.72

Total cost of Production=$319475.79
Total Power Loss = 232.8340MW

Table VIII Comparison of results for 6 UNIT System

METHOD	TOTAL LOSS (MW)	TOTAL COST ($)
LI	237.4495	319565.79
GA	233.1986	319553.21
PSO	235.5858	320135.86
DE	232.8340	319475.79
ABC	233.0993	319496.21

VI. CONCLUSIONS

The differential evolution algorithm has been successfully implemented to solve ED problems with the generator constraints as linear equality and inequality constraints and also considering transmission loss. The algorithm is implemented for three units and six units system. From the result, it is clear that the proposed algorithm has the ability

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to find the better quality solution and has better convergence characteristics, computational efficiency and less CPU time per iteration when compared to other methods such as GA, PSO and ABC.

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BIOGRAPHIES

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