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Differential Evolution Algorithm for Generation Scheduling Considering Valve Point Effects

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ABSTRACT

Power system operation involves some kind of optimization for ensuring economy, security and stability. Economic load dispatch is one such optimization problems and it is applied for minimizing the total fuel cost. Optimizing the fuel cost is done by properly setting the real power generation from the generators in a power system. Differential evolution is a simple and efficient evolutionary algorithm for function optimization over continuous spaces. This paper proposes DE algorithm for solving economic load dispatch problems that take into account nonlinear generator features such as valve point effect .The results are compared with other optimization techniques such as Particle Swarm Optimization, Genetic Algorithm and its efficiency is proved.

Keywords:- Economic load dispatch, fuel cost minimization, valve point effects, Differential algorithm

Introduction

The main aim of electric power utilities is to provide high-quality reliable power supply to the consumers at the lowest possible cost while operating to meet the limits and constraints imposed on the generating units. This formulates the economic load dispatch (ELD) problem for finding the optimal combination of the output power of all the online generating units that minimizes the total fuel cost, while satisfying an equality constraint and a set of inequality constraints. As the cost of power generation is exorbitant, an optimum dispatch results in economy. Practically, the real world input output characteristics of the generating units are highly nonlinear, non-smooth and discrete in nature owing to prohibited operating zones, ramp rate limits and multi-fuel effects. Thus the resultant ELD is a challenging non-convex optimization problem, which is difficult to solve using the traditional methods.

In the traditional ED problem, the cost function for each generator has been approximately represented by a single quadratic function[1] 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 genetic algorithm (GA), Particle swarm optimization (PSO), Simulated Annealing (SA) and Differential evolution optimization.

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 and suffers from local minima problem. 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) [5] is motivated by social behavior 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.

Simulated annealing (SA)[6] is a global optimization method that distinguishes between different local optima. Starting from an initial point, the algorithm takes a step and the function is evaluated. Since the algorithm makes very few assumptions regarding the function to be optimized, it is quite robust with respect to non-quadratic surfaces. In fact, simulated annealing can be used as a local optimizer for difficult functions. The disadvantage of SA is its repeated annealing with a schedule is very slow, especially if the cost function is expensive to compute. The method cannot tell whether it has found an optimal solution.

This paper proposed the DE algorithm for solving the ED problem. The DE[13], one of popular optimization methods, was introduced by Storn and Price in 1995. This algorithm has high efficiency for solving continuous nonlinear optimization problems and multimodal environments[14 15] . The advantages of the DE are simple structure, a few control parameters and high reliable convergences. The DE is one type of modern optimization techniques, which based on a population searching mechanism like as GA[9] , bee colony (BC)[16] optimization and PSO[17 18].

Economic Load Dispatch Formulation

The main objective of the ED problem is to determine minimum generation cost of the generating units, according to the operating constraints of the generators and the power system limits. The simplified fuel cost function of generators represent as quadratic functions, given in equation (1).

$F_i(P_i^t)=a_i+b_iP_i^t+c_i(P_i^t)^2$ (1)

where *ai* , *bi* and *ci* are cost coefficients of generating unit *i* , *Pi* is the real power output of generating unit *i* , *Fi* (*Pi)* is the operating fuel cost of generating unit *i*. Minimizing the fuel cost function (1) of all generating units in the power system is the objective of ED problem which represents as (2)

$\min F= {}^{n}\sum_{i=1} F_i(P_i)$ (2)

where F_T is total fuel cost, *n* is number of generating units.

To satisfy various constraints **:-**

$P_{i,min}<= P_i<= P_{i,max}$ (3)

Power balance constraint

${}^{n}\sum_{i=1}^{n} Pi=D+P_l$ (4)

where *D* is total load demand, *PL* is total transmission line loss, $P_{i,min}$, $P_{i,max}$ are minimum and maximum power output of unit *i* . The effects of multi-valves steam turbine produce a ripple curve on quadratic fuel cost functions and represented as rectified sinusoidal function [1]. Considering the valve point loading effects, the quadratic cost function in (1) was modified as equation(5)

$Fi (Pi) = a_i + b_iP_i + c_iP_i^2 + e_{i1} \sin(f_{i1}(P_{i,min} + P_i))$ (5)

where e_{ik} and f_{ik} are cost coefficients of generating unit *i* **.**

Optimization using Differential Evolution algorithm

Differential Evolution is one of the most recent population based stochastic evolutionary optimization techniques. Storn and Price first proposed DE in 1995[7 8] 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**.**

Initialization and structure of individuals

In the initialization process, a set of individuals is created at random. In this paper, the structure of an individual for auction problem is composed as a set of elements (i.e., generator outputs). Therefore, individual's j's position at iteration 0 can be represented as the vector of $P_j^0=\left[P_{j1}^0,P_{j2}^0,\ldots,P^0{}_{jN_g}\right]$.Where N_g is the number of generator. The summation of all element of individual j $(i.e\sum_{i=1}^{Ng}P^0{}_{i,j}=P_d)$ should be equal to the total system demand P_d and the created element i of individual j at random that should be located within boundary. Although we can create element i of individual j at random satisfying the equality and inequality constraints by mapping [0,1] into $[P_{i\min},P_{i\max}]$. To do this, the following procedure is suggested for any individual in a group.

Evaluate the fitness value

The fitness value of each individual is calculated by using equation

$$f(P_j)=a_j+b_jP_j+c_jP_j^2+\left|e_j\times\sin(f_j\times(P_{i\min}-P_j))\right|$$

Mutation

The mutation operator creates mutant vectors $\left(P_j^{'}\right)$ by perturbing a randomly selected vector (P_a) with the difference of two other randomly selected vectors (P_b and P_c).

$$P_j^{'(G)}=P_a^{(G)}+F\left(P_b^{(G)}-P_c^{(G)}\right)\quad j=1......N_p$$

Where P_a, P_b and Pc, are randomly chosen vectors $\in\{1,....,N_p\}$ and $a\neq b\neq c\neq j$. Pa, P_b and P_c, are selected a new for each parent vector .The scaling constant (F) is an algorithm control parameter used to control the perturbation size in the mutation operator and improve algorithm convergence.

CrossoverThe crossover operation generates trial vector ($P_j^{''}$) by mixing the parameter of the mutant vector with the target vector (P_i), according to a selected probability distribution**.**

$$P''^{(G)}_{i,j} = \begin{cases} P'^{(G)}_{i,j}, if \eta'_i \le C_R ori = q \\ P^{(G)}_{i,j}, otherwise \end{cases}$$

Where $j = 1.....N_p$ and $i = 1...D$; q is randomly chosen index $\in \{1,...., N_p\}$ that guarantees that the trial vector gets at least one parameter from the mutant vector; η'_i is a uniformly distributed random number within [0, 1] generated a new for each values of j. Crossover constant C_R is an algorithm parameter that control the diversity of the population and aids the algorithm to escape from local optima. $P^{(G)}_{i,j}, P'^{(G)}_{i,j}$ and $P''^{(G)}_{i,j}$ are the i^{th} parameter of the j^{th} target vector, mutant vector, and trial vector at generation G, respectively.

Selection

Finally, the selection operator determines the population by choosing between the trial vectors and their predecessors (target vectors) those individuals that presents fitness or are more optimal according to

$$P^{(G+1)}_j = \begin{cases} P''^{(G)}_j iff\left(P''^{(G)}_j\right) \le f\left(P^{(G)}_j\right) \\ P^{(G)}_j, otherwise \end{cases}, j = 1.....N_p$$

The objective of deregulated power market is to minimize the costs of power production for the system subject to power balance constraints, generation limits and market clearing price.

Stopping Criteria

There are various criteria available to stop a stochastic optimization algorithm. Some examples are tolerance, number of function evaluations and number of iterations. In this paper, to compare with the previous results, maximum number of iterations is chosen as the stopping criterion. If the stopping criterion is not satisfied, the above procedure is repeated from step 2 with incremented G value. Otherwise, $P^{(G+1)}_j$ is the optimum generation schedule and $f\left(P''^{(G+1)}_j\right)$ is the minimum generation cost of auction dispatch problem.

Results and discussion

Proposed DE algorithm has been applied to ED problem in a 3- unit system. Here the results obtained are compared for different crossover ratio as well as for different mutation factor. The results obtained are also compared with other optimization technique such as GA,PSO,TSA and BC. The Economic load dispatch problem has been solved using DE algorithm and is implemented in MATLAB environment and is executed on an Intel I5 processor and the results are verified with other optimization algorithms.

Data of the Test System

This section proposes parameters tuning of the DE algorithm to solve the ED problem. Three thermal generating units considering the valve-point loading effects in fuel cost function are tested and shown in Table I [10-12].

P_i(MW)	P_{min}	P_{max}	a	b	c	e	f
P_1	100	600	561	7.92	0.00156	300	0.0315
P_2	100	400	310	7.85	0.00194	200	0.042
P_3	50	200	78	7.94	0.00482	150	0.063

Table-1

Empirical Test Of The Proposed DE

Table-2

F=0.8 CROSSOVER RATIO	Minimum Generation Cost ($/hr)	Elapsed Time(sec)
0.1	8250.524	0.438
0.2	8234.071	0.456
0.3	8234.071	0.546
0.4	8234.071	0.420
0.5	8234.071	0.412
0.6	8234.071	0.402
0.7	8234.071	0.410
0.8	8250.071	0.406
0.9	**8234.071**	**0.355**

Empirical Test of F (Mutant factor) for the proposed DE

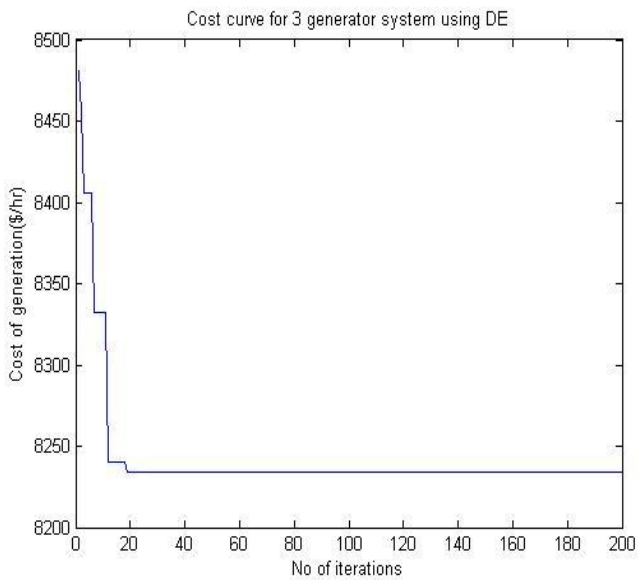
Table-3

CROSSOVER RATIO=0.9 F(MUTANT FACTOR)	MINIMUM GENERATION COST($/hr)	ELAPSED TIME (sec)
0.8	**8234.071**	**0.355**
1	8251.72	0.385
1.1	8234.217	0.398
1.2	8242.16	0.421
2	8242.16	0.385

Comparison of DE results with other methods

Table-4

METHODS	MINIMUM GENERATION COST ($/hr)	ELAPSED TIME (sec)
SA[10]	8234.15	-
PS[11]	8234.05	0.81
MFEB[12]	8234.08	8.0
GAF[12]	8234.07	24.65
GAB[12]	8234.08	35.8
IFEP[12]	8234.07	6.78
CEP[12]	8234.07	20.46
FEP[12]	8234.07	4.45
GA[19]	8234.073	1.05
PSO[19]	8234.076	1.65
TSA[19]	8234.073	8.62
BC[19]	8234.083	2.02
DE	**8234.071**	**0.355**



Conclusion

The differential evolution algorithm has been successfully implemented to solve ED problems with the generator constraints as linear equality and inequality constraints . The algorithm is implemented for three units system. From the result, it is clear that the proposed algorithm has the ability 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,SA,TSA,BC,FEP,CEP,SA,PS,MFEB,GAF,GFB and IFEP.

References

i. *A.J. Wood and B. F. Wollenberg, Power Generation, Operation and Control, 2nd Edition, New York: John Wiley & Sons, 1996.*

ii. *J. B. Park, K. S. Lee, J. R. Shin and K. Y. Lee, "A particle swarm optimization for economic dispatch with non-smooth cost functions", IEEE Trans. on Power Systems, Vol. 8, No. 3, pp. 1325-1332, Aug. 1993.*

iii. *Z. X. Liang and J. D. Glover, "A zoom feature for a dynamic programming solution to economic dispatch including transmission losses", IEEE Trans. on Power Systems, Vol. 7, No. 2, pp. 544-550, May 1992.*

iv. *K. Deb, "An efficient constraint handling method for genetic algorithms", Computer Methods in Applied Mechanics and Engineering, Elsevier, Netherlands, 186(2- 4):311–338, 2000.*

v. *J. Kennedy and R. C. Eberhart, "Particle Swarm Optimization", In Proceedings of 1995 IEEE International Conference on Neural Networks, 4: 1942–1948, Perth, Western Australia, 1995. .*

vi. *K. P. Wong and C. C. Fung, "Simulated Annealing based Economic Dispatch Algorithm", Proc. Inst. Elect. Eng., Gen. Transm. and Distrib., vol. 140, no. 6, pp. 509–515, November 1993. .*

vii. *R. Storn and K. Price, "Differential evolution: a simple and efficient adaptive scheme for global optimization over continuous spaces", Technical Report TR-95-012, Berkeley, USA: International Computer Science Institute, 1995.*

viii. *K. Vaisakh and L. R. Srinivas, "Differential Evolution Approach for Optimal Power Flow Solution", Journal of Theoretical and Applied Information Technology.*

ix. *D. E. Goldberg, Genetic Algorithms in Search, Optimization and Machine Learning, MA: Addison-Wesley Publishing Company Inc.,1989.*

x. *K.P. Wong 'Solving power system optimization problems using simulated annealing', Engng Applic. Artif.Intell. vol. 8, no. 6, pp. 665-670, 1996.*

xi. *J.S. Al-Sumait, A.K AL-Othman and J.K. Sykulski, "Application of pattern search method to power system valve-piont economic dispacth", Int. J. Electr Power Energy Syst (2007), doi:10.1016/j.ijepes.2007.06.016*

xii. *N. Sinha, R. Chakrabarti and P.K. Chattopadhyay "Evolutionary programming techniques for economic load dispatch," IEEE Trans. Evol. Comput, vol. 7, no. 1, pp. 83-94, 2003.*

xiii. *R. Storn and K.V. Price, "Differential evolution a simple and efficient heuristic for global optimization over continuous space," J. Global Optim, vol. 11, no. 4, pp. 341-359, 1997.*

xiv. *K.V. Price, R.M. Storn, J.A. Lampinen, "Differential evolution; A practical approach to global optimization," Springer Berlin, Heidelberg, 2005.*

xv. *R. Storn, "System design by constraint adaptation and differential evolution," IEEE Trans. Evol. Comput, vol. 3, no. 1, pp. 22-34, 1999.*

xvi. *D.T. Pham, A. Ghanbarzadeh, E. Koc, S. Otri, S. Rahim and M. Zaidi "The bees algorithm, a novel tool for complex optimization problems". Proc 2nd Int Virtual Conf. Intelligent Prod. Mach. and Syst, Oxford, Elsevier, pp.454-459, 2006.*

xvii. *J.F. Kenedy and R.C. Eberhart, "particle swarm optimization," In: Proc IEEE international conference on neural networks, vol. 4, pp. 1942- 1948, 1995.*

xviii. *M. Clerc and J.K. Kenedy, "The particle swarm: Explosion, stability and convergence in a multi - dimensional complex space," IEEE Trans. Evol. Comput, vol. 2, no. 3, pp. 91-96, 1998. World Academy of Science, Engineering and Technology 28 2009*

xix. *S. Khamsawang and S. Jiriwibhakorn, "Solving the economic dispatch problem by using Differential evolution" World Academy of Science, Engineering and Technology 28 2009.*

xx. *C.Kumar, T.Alwarsamy ," Solution of Economic Dispatch Problem using Differential Evolution Algorithm" International Journal of Soft Computing and Engineering (IJSCE) ISSN: 2231-2307, V*

xxi. *olume-1, Issue-6, January 2012.*