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Research Article

Dynamic Economic Dispatch Using Hybrid DE-SQP for Generating Units with Valve-Point Effects

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This paper presents hybrid differential evolution (DE) and sequential quadratic programming (SQP) for solving the dynamic economic dispatch (DED) problem for generating units with valve-point effects. DE is used as a global optimizer and SQP is used as a fine tuning to determine the optimal solution at the final. The feasibility of the proposed method is validated with five- and ten-unit test systems. Results obtained by DE-SQP method are compared with other techniques in the literature.

1. Introduction

The primary objective of the static economic dispatch (SED) problem of electric power generation is to determine the optimal schedule of online generating units' outputs so as to meet the load demand at a certain time at the minimum operating cost under various system and generator operational constraints. Plant operators, to avoid life-shortening of the turbines and boilers, try to keep thermal stress on the equipments within the safe limits. This mechanical constraint is usually transformed into a limit on the rate of change of the electrical output of generators. Such ramp rate constraints link the generator operation in two consecutive time intervals. Optimal dynamic dispatch problem is an extension of SED problem which is used to determine the generation schedule of the committed units so as to meet the predicted load demand over a time horizon at minimum operating cost under ramp rate constraints and other constraints (see [1–31]). Since the ramp rate constraints couple the time intervals, the optimal dynamic dispatch problem is a difficult optimization problem. If the ramp rate constraints are not included in the optimization problem, the optimal dynamic dispatch problem is reduced to a set of uncoupled SED problems that can be easily solved.

Optimal dynamic dispatch problem was first formulated by Bechert and Kwatny [1] in 1972 and was followed by [2–5]. In these papers, the problem was formulated as an optimal control problem. The optimal control dynamic dispatch formulation models the power system generation by means of state equations where the state variables are the electrical power outputs of the generators and the control inputs are the ramp rates of the generators. In this approach, the optimization is done with respect to the ramp rates and the solution produces an optimal output generator trajectory for a given initial generation. Since the 1980s, the optimal dynamic dispatch problem has been formulated as a minimization problem of the total cost over the dispatch period under some constraints and has been known as the dynamic economic dispatch (DED) problem (see [6–31]). Since the DED problem was introduced, several optimization techniques and procedures have been used for solving the DED problem with complex objective functions or constraints (see the review paper [6]). There were a number of classical methods that have been applied to solve this problem such as the lambda iterative method [16], gradient projection method [25], Lagrange relaxation [26], linear programming [24], and interior point method [11, 13]. Most of these methods are not applicable for nonsmooth or nonconvex cost functions. To overcome this problem, many stochastic optimization methods have been employed to solve the DED problem, such as simulated annealing (SA) [27], genetic algorithms (GA) [28], differential evolution (DE) [18, 19], particle swarm optimization (PSO) [10, 31], and artificial immune system (AIS) [15]. Many of these techniques have proven their effectiveness in solving the DED problem without any or fewer restrictions on the shape of the cost function curves. Hybrid methods which combine two or more optimization methods have been successfully applied to DED problems with valve-point effects such as EP-SQP [9] and PSO-SQP [29, 30].

DE which was proposed by Storn and Price [32] is a population-based stochastic parallel search technique. DE uses a rather greedy and less stochastic approach to problem solving compared to other evolutionary algorithms. DE has the ability to handle optimization problems with nonsmooth/nonconvex objective functions [32]. Moreover, it has a simple structure and a good convergence property, and it requires a few robust control parameters [32]. DE has been successfully applied to the DED problem with nonsmooth and nonconvex cost functions (see [18–21]).

DE is one of the good methods which have been used for solving the DED problem with nonsmooth and nonconvex cost functions; however, the obtained solutions are just near global optimum with long computation time. Therefore, hybrid methods such as DE-SQP can be effective in solving the DED problem with valve-point effects. The aim of this paper is to propose hybrid DE-SQP method to solve the DED problem with valve-point effects. DE is used as a base level search for global exploration and SQP is used as a local search to fine-tune the solution obtained from DE. In the DE-SQP techniques, DE will thoroughly search the solution space and stops when the specified maximum iteration count is reached. Thereafter, the SQP technique will be used to fine-tune the final solution obtained by the DE method.

The remainder of this paper is organized as follows: in Section 2, we introduce the DED problem formulation. An overview of the differential evolution and sequential quadratic programming algorithms is presented in Sections 3 and 4. In Section 5, numerical examples and simulation results are presented. Finally, conclusions are drawn in Section 6.

2. Formulation of the DED Problem

The objective of the DED problem is to determine the generation levels for the committed units which minimize the total fuel cost over the dispatch period $[0, T]$,

$$\min C_T = \sum_{t=1}^{T}\sum_{i=1}^{N} C_i\left(P_i^t\right) \tag{2.1}$$

subject to the following constraints:

(i) power balance constraint:

$$\sum_{i=1}^{N} P_i^t = D^t + \text{Loss}^t, \quad t = 1, \ldots, T, \tag{2.2}$$

(ii) generation limits:

$$P_i^{\min} \leq P_i^t \leq P_i^{\max}, \quad i = 1, \ldots, N, \ t = 1, \ldots, T, \tag{2.3}$$

(iii) generating unit ramp rate limits:

$$-DR_i \leq P_i^t - P_i^{t-1} \leq UR_i, \quad i = 1, \ldots, N, \ t = 2, \ldots, T, \tag{2.4}$$

where N is the number of committed units; T is the number of intervals in the time horizon; P_i^t is the generation of unit i during the tth time interval $[t-1, t)$; D^t is the demand at time t (i.e., the t-th time interval); UR_i and DR_i are the maximum ramp up/down rates for unit i; $P_i^{\min}$ and $P_i^{\max}$ are the minimum and maximum capacity of unit i, respectively. The fuel cost of unit i considering valve-point effects can be expressed as

$$C_i\left(P_i^t\right) = a_i + b_i P_i^t + c_i\left(P_i^t\right)^2 + \left|d_i \sin\left(e_i\left(P_i^{\min} - P_i^t\right)\right)\right|, \tag{2.5}$$

where a_i, b_i, and c_i are positive constants, and d_i and e_i are the coefficients of unit i reflecting valve-point effects.

The B-coefficient method is one of the most commonly used by power utility industry to calculate the network losses. In this method, the network losses are expressed as a quadratic function of the unit's power outputs that can be approximated by

$$\text{Loss}^t = \sum_{i=1}^{N}\sum_{j=1}^{N} P_i^t B_{ij} P_j^t, \quad t = 1, \ldots, T, \tag{2.6}$$

where B_{ij} is the ijth element of the loss coefficient square matrix of size N.

3. Overview of Differential Evolution Algorithm

DE is a simple yet powerful heuristic method for solving nonlinear, nondifferentiable, and nonsmooth optimization problems. DE algorithm is a population-based-algorithm using three operators mutation, crossover, and selection to evolve from randomly generated initial population to final individual solution. The key idea behind DE is that it starts with an initial population of feasible target vectors (parents) and new solutions (offsprings) are generated (by mutation, crossover, and selection operations) until the optimal solution is reached. In the mutation operation, three different vectors are selected randomly from the population and a mutant vector is created by perturbing one vector with the difference of the two other vectors. In the crossover operation, a new trial vector (offspring) is created by replacing certain parameters of the target vector by the corresponding parameters of the mutant vector on the bases of a probability distribution. In DE, the competition between the parents and offspring is one to one. The individual with best fitness will remain till the next generation. The iterative process continues until a user-specific stopping criterion is met. DE algorithm has three control parameters, which are differentiation (or mutation) factor F, crossover constant CR, and size of population N_P. According to Storn and Price [32], the basic strategy of DE for m-dimensional optimization problem can be described as follows.

(1) Initialization: generate a population of N_P initial feasible target vectors (parents) $X_i = \{x_{1i}, x_{2i}, \ldots, x_{mi}\}$, $i = 1, 2, \ldots, N_P$ randomly as

$$x_{ji} = x_j^{\min} + s_1 \cdot \left(x_j^{\max} - x_j^{\min}\right), \quad j = 1, 2, \ldots, m, \; i = 1, 2, \ldots, N_P, \tag{3.1}$$

where s_1 is uniform random number in $[0, 1]$; $x_j^{\min}$ and $x_j^{\max}$ are the lower and upper bounds of the jth component of the target vector.

(2) Mutation: let $X_i^G = \{x_{1i}^G, x_{2i}^G, \ldots, x_{mi}^G\}$ be the individual i at the current generation G. A mutant vector $V_i^{G+1} = (v_{1i}^{G+1}, v_{2i}^{G+1}, \ldots, v_{mi}^{G+1})$ is generated according to the following:

$$V_i^{G+1} = X_{r_1}^G + F \cdot \left(X_{r_2}^G - X_{r_3}^G\right), \quad r_1 \neq r_2 \neq r_3 \neq i, \; i = 1, 2, \ldots, N_P \tag{3.2}$$

with randomly chosen integer indexes $r_1, r_2, r_3 \in \{1, 2, \ldots, N_P\}$.

(3) Crossover: according to the target vector X_i^G and the mutant vector V_i^{G+1}, a new trial vector (offspring) $U_i^{G+1} = \{u_{1i}^{G+1}, u_{2i}^{G+1}, \ldots, u_{mi}^{G+1}\}$ is created with

$$u_{ji}^{G+1} = \begin{cases} v_{ji}^{G+1} & \text{if } \left(\operatorname{rand}(j) \leq CR\right) \text{ or } j = rnb(i), \\ x_{ji}^G & \text{otherwise,} \end{cases} \tag{3.3}$$

where $j = 1, 2, \ldots, m$, $i = 1, 2, \ldots, N_P$ and $\operatorname{rand}(j)$ is the jth evaluation of a uniform random number generator between $[0, 1]$. CR is the crossover constant between $[0, 1]$ which has to be determined by the user. $rnb(i)$ is a randomly chosen index from $1, 2, \ldots, m$ which ensures that U_i^{G+1} gets at least one parameter from V_i^{G+1} [32].

(4) Selection: This process determines which of the vectors will be chosen for the next generation by implementing one-to-one competition between the new generated trial vectors and their corresponding parents. The selection operation can be expressed as follows:

$$X_i^{G+1} = \begin{cases} U_i^{G+1} & \text{if } f\left(U_i^{G+1}\right) \le f\left(X_i^G\right), \\ X_i^G & \text{otherwise}, \end{cases} \tag{3.4}$$

where $i = 1, 2, \ldots, N_P$ and f is the objective function to be minimized. The value of f of each trial vector U_i^{G+1} is compared with that of its parent target vector X_i^G. If the value of f, of the target vector X_i^G, is lower than that of the trial vector, the target vector is allowed to advance to the next generation. Otherwise, the target vector is replaced by a trial vector in the next generation. Thus, all the individuals of the next generation are as good as or better than their counterparts in the current generation. The above steps of reproduction and selection are repeated generation after generation until some stopping criteria are satisfied.

In this paper, we define the evaluation function for evaluating the fitness of each individual in the population in DE algorithm as follows:

$$f = C_T + \lambda \sum_{t=1}^{T} \left(\sum_{i=1}^{N} P_i^t - \left(D^t + \mathrm{Loss}^t\right) \right)^2, \tag{3.5}$$

where λ is a penalty value. Then the objective is to find $f_{\min}$, the minimum evaluation value of all the individuals in all iterations. The penalty term reflects the violation of the equality constraint. Once the minimum of f is reached, the equality constraint is satisfied. Also, the generation power output of each unit at time t should be adjusted to satisfy the following constraints which combine constraints (2.3) and (2.4) as

$$P_i^t = \begin{cases} P_i^{t,\min} & \text{if } P_i^t < P_i^{t,\min}, \\ P_i^t & \text{if } P_i^{t,\min} \le P_i^t \le P_i^{t,\max}, \\ P_i^{t,\max} & \text{if } P_i^t > P_i^{t,\max}, \end{cases} \tag{3.6}$$

where

$$\begin{gathered} P_i^{t,\min} = \begin{cases} P_i^{\min} & \text{if } t = 1, \\ \max\left(P_i^{\min}, P_i^{t-1} - DR_i\right) & \text{others}, \end{cases} \\ P_i^{t,\max} = \begin{cases} P_i^{\max} & \text{if } t = 1, \\ \min\left(P_i^{\max}, P_i^{t-1} + UR_i\right) & \text{others}. \end{cases} \end{gathered} \tag{3.7}$$

4. Sequential Quadratic Programming

SQP method can be considered as one of the best nonlinear programming methods for constrained optimization problems. It outperforms every other nonlinear programming method in terms of efficiency, accuracy, and percentage of successful solutions over a

Table 1: Hourly generation (MW) schedule of 5-unit system with losses (MW) using DE-SQP.

Hour	P_1	P_2	P_3	P_4	P_5	Loss
1	21.6845	99.3693	113.2191	40.0047	139.3571	3.6348
2	10.0001	98.4091	112.8296	78.0092	139.7746	4.0225
3	10.0000	93.0102	112.6376	124.5983	139.5085	4.7547
4	10.0208	98.9394	112.7739	174.5821	139.6980	6.0141
5	10.0000	94.6503	111.1824	209.3376	139.5944	6.7647
6	39.9323	98.7250	112.7829	210.1512	154.2991	7.8906
7	10.0000	98.0631	112.7434	209.7011	203.9654	8.4729
8	12.5522	98.9663	112.9829	209.5933	229.1619	9.2567
9	42.5522	101.9286	114.7389	210.6817	230.2829	10.1843
10	64.8347	98.4322	112.3767	209.6753	229.2401	10.5591
11	75.0000	100.3215	114.8471	211.1004	229.7591	11.0283
12	75.0000	98.9111	112.9582	234.6857	230.1685	11.7235
13	64.2203	97.9704	112.5101	210.1351	229.7242	10.5602
14	50.0381	98.4511	112.5499	209.7742	229.3542	10.1675
15	35.4162	98.8278	112.6282	186.4410	229.8143	9.1277
16	10.0000	98.4782	112.6986	136.4410	229.6153	7.2332
17	10.0000	88.2951	112.6200	124.6074	229.1609	6.6833
18	35.3553	98.7119	112.7691	139.3772	229.6497	7.8633
19	33.6668	98.5493	111.9794	189.3772	229.5668	9.1396
20	63.6668	98.5990	112.5890	210.0303	229.6762	10.5612
21	39.2846	98.5966	112.7120	209.8748	229.4336	9.9017
22	10.0437	98.6538	112.9970	161.5680	229.6066	7.8692
23	10.0000	98.8754	112.6148	124.7293	186.6872	5.9067
24	10.0000	81.0109	112.1181	124.8490	139.5118	4.4899

large number of test problems. The method closely resembles Newton's method for constrained optimization, just as is done for unconstrained optimization. At each iteration, an approximation of the Hessian of the Lagrangian function is made using Broyden-Fletcher-Goldfarb-Shanno (BFGS) quasi-Newton updating method. The result of the approximation is then used to generate a quadratic programming (QP) subproblem whose solution is used to form a search direction for a line search procedure. Since the objective function to be minimized is nonconvex, SQP ensures a local minimum for an initial solution. SQP has been combined with stochastic optimization techniques to constitute hybrid methods for solving the DED problem with nonsmooth cost functions (see [9, 22]). In this paper, DE is used as a global search and finally the best solutions obtained from DE is given as initial condition for SQP method as a local search to fine-tune the solution. SQP simulations are computed by the fmincon code of the MATLAB Optimization Toolbox.

5. Simulation Results

In this paper, to assess the efficiency of the proposed DE-SQP method, two case studies (5 units with losses and 10 units without losses, resp.) of DED problems have been considered in which the objective functions are nonsmooth. In each case study, the simulation parameters chosen are population size $N_P = 60$, maximum iteration $G_{\max} = 20000$, mutation factor

Table 2: Hourly generation (MW) schedule of 10-unit system without losses using DE-SQP.

Hour	P_1	P_2	P_3	P_4	P_5	P_6	P_7	P_8	P_9	P_{10}
1	226.2680	135.0000	73.3721	64.0280	123.9052	123.9200	129.7852	84.7215	20.0000	55
2	223.7127	137.2833	75.0068	114.0280	173.5295	126.5124	129.8165	55.0235	20.0871	55
3	301.2838	217.1962	148.4157	64.4870	123.8118	120.6932	129.5217	77.5907	20.0000	55
4	302.6657	225.8898	197.9257	114.4870	122.4412	160.0000	130.0000	47.5907	50.0000	55
5	302.9885	305.7038	217.5037	119.5778	122.8379	159.9003	129.4879	47.0000	20.0000	55
6	379.2909	308.5845	297.3863	125.2933	172.8379	122.3651	99.4879	47.7542	20.0000	55
7	376.1425	313.2181	299.8249	175.2933	124.3167	160.0000	100.2252	77.7542	20.2252	55
8	455.9173	392.9929	246.5742	130.5711	170.4569	119.9589	130.0000	54.5287	20.0000	55
9	456.3707	401.4499	326.5742	180.5711	173.0766	124.5330	101.8959	84.5287	20.0000	55
10	383.4956	400.8323	328.1355	230.5711	221.4583	160.0000	127.9784	114.5287	50.0000	55
11	455.4912	460.0000	302.9254	245.0551	173.4924	160.0000	128.7601	85.2758	80.0000	55
12	457.9600	460.0000	339.5183	237.7736	223.4387	160.0000	129.3094	77.0000	80.0000	55
13	454.8727	460.0000	300.1122	187.7918	229.2453	160.0000	127.9416	47.0182	50.0182	55
14	378.7648	389.8503	298.0170	226.9459	218.6326	160.0000	129.6473	47.0711	20.0711	55
15	380.4469	309.8503	284.0959	176.9459	221.4171	122.4799	128.8134	76.9505	20.0000	55
16	300.6291	309.9676	204.7668	187.0835	173.1144	126.1948	130.0000	47.1326	20.1112	55
17	305.6309	309.8471	185.3632	186.0791	123.1144	118.3037	129.2531	47.4085	20.0000	55
18	305.1398	311.8823	216.0384	236.0227	124.3315	122.3716	129.9350	77.3435	49.9350	55
19	383.3568	313.4480	293.2465	233.9297	173.3850	121.5403	128.3334	53.7371	20.0233	55
20	385.2071	393.3921	339.9674	281.5235	223.3292	159.9674	129.9320	83.6812	20.0000	55
21	383.3007	395.5746	289.7491	231.5539	222.3756	119.5615	129.8692	76.9978	20.0176	55
22	303.9705	385.3051	209.7887	181.5935	172.4152	122.9631	99.9088	47.0374	50.0176	55
23	224.3924	305.3051	175.5064	131.5960	122.4177	124.8285	95.9138	77.0000	20.0399	55
24	150.0000	225.3051	186.0551	180.6403	73.3908	121.6506	124.9581	47.0000	20.0000	55

$F = 0.423$, and crossover factor $CR = 0.885$ and the results represent the average of 30 runs of the proposed method. All computations are carried out by MATLAB program.

5.1. *Five-Unit System*

This example presents an application of the DE-SQP method to the DED problem consisting of five units with valve point effects and transmission line losses. The technical data of the units are taken from [17]. The optimal solution of the DED problem among 30 runs is over, for example, 24 h $(T = 24)$, and is given in Table 1.

5.2. *Ten-Unit System*

This example presents an application of the DE-SQP method to the DED problem consisting of ten units without losses. The data of the ten-unit system are taken from [9]. The optimal solution of the DED problem is over, for example, 24 h $(T = 24)$, and is given in Table 2.

Comparisons between our proposed method (DE-SQP) and other methods for both examples (five units with losses and ten units without losses) are given in Table 3. It is observed that the proposed method reduces the total generation cost better than the other methods reported in the literature. These methods can be classified into (1) heuristic methods such as pattern search [23], particle swarm optimization [17], differential evolution [18],

Table 3: Comparison of the results with other methods.

Optimization technique	5-unit system with losses		10-unit system without losses
	Cost ($)	Total losses (MW)	Cost ($)
Pattern search [23]	46530	192.21	—
Particle swarm optimization [17]	47852	—	—
Differential evolution [18]	45800	194.35	—
Sequential quadratic programming [9]	—	—	1051163
Evolutionary programming [9]	—	—	1048638
Hybrid evolutionary programming and Sequential quadratic programming [9]	—	—	1031746
Modified differential evolution [20]	—	—	1031612
Hybrid particle swarm optimization and Sequential quadratic programming [30]	—	—	1030773
Proposed hybrid differential evolution and Sequential quadratic programming	43231	193.81	1030500

evolutionary programming [9], and modified differential evolution [20], (2) mathematical programming-based methods such as sequential quadratic programming [9], and (3) hybrid methods such as hybrid evolutionary programming and sequential quadratic programming [9], and hybrid particle swarm optimization and sequential quadratic programming [30]. Moreover, it is observed that the transmission line losses calculated by our method are smaller than those of other methods. For more details about these methods and their way of working we refer the reader to the review paper [6].

6. Conclusion

This paper presents hybrid method, combining differential evolution (DE), and sequential quadratic programming (SQP) for solving the DED problem with valve-point effects. At first we, applied DE to find the best solution, then this best solution is given to SQP as an initial condition to fine-tune the optimal solution at the final. The feasibility and efficiency of the DE-SQP method are illustrated by conducting two examples consisting of five and ten units with valve-point effects, respectively. Our results are compared with other methods. It has been shown that our proposed methods give less cost than other methods reported in the literature.

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