

Adaptive Differential Evolution Approach for Constrained Economic Power Dispatch with Prohibited Operating Zones

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Abstract

Economic power dispatch (EPD) is one of the main tools for optimal operation and planning of modern power systems. To solve effectively the EPD problem, most of the conventional calculus methods rely on the assumption that the fuel cost characteristic of a generating unit is a continuous and convex function, resulting in inaccurate dispatch. This paper presents the design and application of efficient adaptive differential evolution (ADE) algorithm for the solution of the economic power dispatch problem, where the non-convex characteristics of the generators, such as prohibited operating zones and ramp rate limits of the practical generator operation are considered. The 26 bus benchmark test system with 6 units having prohibited operating zones and ramp rate limits was used for testing and validation purposes. The results obtained demonstrate the effectiveness of the proposed method for solving the non-convex economic dispatch problem.

Keywords

Economic Power Dispatch; Differential Evolution; Power System Optimization; Prohibited Operating Zone.

Introduction

The conventional economic power dispatch (EPD) problem of power generation

involves allocation of power generation to different thermal units to minimize the operating cost subject to diverse equality and inequality constraints of the power system. This makes the EPD problem a large-scale highly nonlinear constrained optimization problem.

The EPD problem has been solved via many traditional techniques, such as linear programming, nonlinear programming, quadratic programming, Newton-based techniques and interior point methods. Usually, these methods rely on the assumption that the fuel cost characteristic of a generating unit is a smooth, convex function. However, there are situations where it is not possible, or appropriate, to represent the unit's fuel cost characteristic as a convex function. For example, this situation arises when valve-points, unit prohibited operating zones, or multiple fuels are present. Hence, the true global optimum of the problem could not be reached easily. New numerical methods are then needed to cope with these difficulties, specially, those with high speed search to the optimal and not being trapped in local minima.

In recent years, new optimization techniques based on the principles of natural evolution, and with the ability to solve extremely complex optimization problems, have been developed. These techniques, also known as evolutionary algorithms, search for the solution of optimization problems, using a simplified model of the evolution process found in nature [1]. Differential Evolution (DE) is one of these recently developed evolutionary computation techniques [2, 3]. Differential evolution improves a population of candidate solutions over several generations using the mutation, crossover and selection operators in order to reach an optimal solution. Differential evolution presents great convergence characteristics and requires few control parameters, which remain fixed throughout the optimization process and need minimum tuning [4].

In this paper, an adaptive differential evolution (ADE) based technique is presented and used to solve the economic dispatch problem, with non-convex, non-continuous, and non-linear cost functions. An application was performed on the 6-unit benchmark test system, with ramp rate limits and prohibited operating zones. The results obtained through ADE and those of the previous methods are compared. The outcome of the comparisons confirms the effectiveness of the proposed ADE approach in terms of solution quality, consistency and computation rapidity.

Basic Economic Power Dispatch Formulation

The objective of EPD is to minimize the total generation cost of a power system over some appropriate period (one hour typically) while satisfying various constraints. Mathematically, this becomes a constrained optimization problem, which can then be written in the following form:

$$\text{Minimize } F(x) \quad (4)$$

$$\text{Subject to: } g(x) = 0 \quad (2)$$

$$\text{Subject to: } h(x) \leq 0 \quad (3)$$

$F(x)$ is the objective function; $g(x)$ and $h(x)$ are respectively the set of operation constraints. x is the vector of control and state variables.

Objective Function

The objective function for the ELD reflects the cost associated with generating power in the system. The objective function for the entire power system can then be written as the sum of the fuel cost model for each generator, a follows:

$$F(x) = \sum_{i=1}^{ng} F_i \quad (4)$$

where ng is the number of online generating units. F_i is the fuel cost function of the i^{th} generator in (\$/h), which is usually expressed as a quadratic polynomial:

$$F_i(P_i) = a_i P_i^2 + b_i P_i + c_i \quad (5)$$

where P_i is the power of generator i . a_i , b_i and c_i are the cost coefficients of generator i .

Power Balance Constraint

The power balance constraint reduces the power system to a basic principle of equilibrium between total system generation and total system loads. Equilibrium is only met when the total system generation equals the total system load P_D plus system losses P_L as it is shown in (6).

$$\sum_{i=1}^{ng} P_i - P_D - P_L = 0 \quad (6)$$

The exact value of the system losses can only be determined by means of a power flow solution. The most popular approach for finding an approximate value of the losses is by

way of Kron's loss formula (7), which approximates the losses as a function of the output level of the system generators.

$$P_L = \sum_{i=1}^{ng} \sum_{j=1}^{ng} P_i B_{ij} P_j + \sum_{i=1}^{ng} P_i B_{i0} + B_{00} \quad (7)$$

Generator Operation Constraints

Generating units have lower and upper production limits, which are directly related to the design of the machine. These bounds can be defined as a pair of inequality constraints, as follows:

$$P_i^{\min} \leq P_i \leq P_i^{\max} \quad (8)$$

where P_i^{\min} and P_i^{\max} are the minimum and maximum generation of unit i , respectively.

Ramp Rate Limit Constraints

In EPD studies, the unit generation output is usually assumed to be adjusted instantaneously. Even though this assumption simplifies the problem, it does not reflect the actual operating processes of the generating unit. Therefore, in practical situations, the operating range of all online units is restricted by their ramp rate limits, for forcing the units operation continually between two adjacent specific periods. The inequality constraints due to ramp rate limits are given by:

(1) if generation increases,

$$P_i - P_i^0 \leq UR_i \quad (9)$$

(2) if generation decreases,

$$P_i^0 - P_i \leq DR_i \quad (10)$$

where P_i and P_i^0 are the current and previous power output of unit i , respectively. UR_i and DR_i are the up and down ramp rate limit of the i^{th} generating unit (in MW/h), respectively.

Prohibited Operating Zones

Prohibited operating zones in the input-output curve of generator are due to steam valve operation or vibration in its shaft bearing. In practice, it is difficult to determine the prohibited zone by actual performance testing or operating records. In actual operation, the best economy is achieved by avoiding operation in these areas [5]. Hence, the feasible

operation zone of unit i can be given as follows:

$$\begin{cases} P_i^{\min} \leq P_i \leq P_{i,1}^L, \\ P_{i,k-1}^U \leq P_i \leq P_{i,k}^L, & k = 1, \dots, nz \\ P_{i,nz}^U \leq P_i \leq P_i^{\max} \end{cases} \quad (11)$$

where $P_{i,k}^L$ and $P_{i,k}^U$ are the lower and upper bound of the k^{th} prohibited zone of generator i

Overview of Differential Evolution Algorithm

The differential Evolution algorithm (DE) is a population based algorithm like genetic algorithm using the similar operators; crossover, mutation and selection. The main difference in constructing better solutions is that genetic algorithms rely on crossover while DE relies on mutation operators. This main operation is based on the differences of randomly sampled pairs of solutions in the population.

The algorithm uses mutation operation as a search mechanism and selection operation to direct the search toward the prospective regions in the search space. The DE algorithm also uses a non-uniform crossover that can take child vector parameters from one parent more often than it does from other. By using the components of the existing population members to construct trial vectors, the recombination (crossover) operator efficiently shuffles information about successful combinations, enabling the search for a better solution space.

DE Optimization Procedure

An optimization task consisting of D parameters can be presented by a D -dimensional vector. In DE, a population of N_p solution vectors is randomly created at the start. This population is successfully improved over G generations by applying mutation, crossover and selection operators, to reach an optimal solution [3, 4]. The main steps of the DE algorithm are given bellow [6]:

```
Initialization
Evaluation
Repeat
Mutation
Crossover
Evaluation
Selection
Until (Termination criteria are met)
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Mutation

The mutation operator creates mutant vectors by perturbing a randomly selected vector \mathbf{x}_a with the difference of two other randomly selected vectors \mathbf{x}_b and \mathbf{x}_c ,

$$\mathbf{x}_i^{(G)} = \mathbf{x}_a^{(G)} + F \cdot (\mathbf{x}_b^{(G)} - \mathbf{x}_c^{(G)}), \quad i=1, \dots, N_P \quad (12)$$

where \mathbf{x}_a , \mathbf{x}_b and \mathbf{x}_c are randomly chosen vectors among the N_P population, and $a \neq b \neq c$. \mathbf{x}_a , \mathbf{x}_b and \mathbf{x}_c are selected anew for each parent vector. The scaling constant F is an algorithm control parameter used to adjust the perturbation size in the mutation operator and improve algorithm convergence.

Crossover

The crossover operation generates trial vectors \mathbf{x}_i' by mixing the parameters of the mutant vectors \mathbf{x}_i' with the target vectors \mathbf{x}_i according to a selected probability distribution,

$$\mathbf{x}_{j,i}^{(G)} = \begin{cases} \mathbf{x}_{j,i}^{(G)}, & \text{if } \rho_j \leq C_R \text{ or } j = q \\ \mathbf{x}_{j,i}^{(G)}, & \text{otherwise} \end{cases} \quad (13)$$

where $i=1, \dots, N_P$ and $j=1, \dots, D$; q is a randomly chosen index $\in \{1, \dots, N_P\}$ that guarantees that the trial vector gets at least one parameter from the mutant vector; ρ_j is a uniformly distributed random number within $[0, 1]$ generated anew for each value of j . The crossover constant C_R is an algorithm parameter that controls the diversity of the population and aids the algorithm to escape from local minima. $\mathbf{x}_{j,i}^{(G)}$ and $\mathbf{x}_{j,i}^{(G)}$ are the j^{th} parameter of the i^{th} target vector, mutant vector, and trial vector at generation G , respectively.

Selection

The selection operator forms the population by choosing between the trial vectors and their predecessors (target vectors) those individuals that present a better fitness or are more optimal according to (10).

$$\mathbf{x}_i^{(G+1)} = \begin{cases} \mathbf{x}_i^{(G)}, & \text{if } f(\mathbf{x}_i^{(G)}) \leq f(\mathbf{x}_i^{(G)}) \\ \mathbf{x}_i^{(G)}, & \text{otherwise} \end{cases}, \quad i=1, \dots, N_P. \quad (14)$$

This optimization process is repeated for several generations, allowing individuals to improve their fitness as they explore the solution space in search of optimal values.

DE has three essential control parameters: the scaling factor (F), the crossover

constant (C_R) and the population size (N_P). The scaling factor is a value in the range $[0, 2]$ that controls the amount of perturbation in the mutation process. The crossover constant is a value in the range $[0, 1]$ that controls the diversity of the population. The population size determines the number of individuals in the population and provides the algorithm enough diversity to search the solution space.

Control Parameter Selection

Proper selection of control parameters is very important for algorithm success and performance. The optimal control parameters are problem specific. Therefore, the set of control parameters that best fit each problem have to be chosen carefully. The most common method used to select control parameters is parameter tuning. Parameter tuning adjusts the control parameters through testing until the best settings are determined. Typically, the following ranges are good initial estimates [7]: $F = [0.5, 0.6]$, $C_R = [0.75, 0.90]$, and $N_P = [3*D, 8*D]$.

Constraint Handling

Since most evolutionary algorithms such as differential evolution were originally conceived to solve unconstrained problems, various constraint-handling techniques have been developed. One possible strategy is to generate and keep control variables in the feasible region as follows [7]:

$$x_{j,i}^{(G)} = \begin{cases} x_{j,i}^{\min}, & \text{if } x_{j,i}^{(G)} \leq x_{j,i}^{\min} \\ x_{j,i}^{\max}, & \text{if } x_{j,i}^{(G)} \geq x_{j,i}^{\max} \\ x_{j,i}^{(G)}, & \text{otherwise} \end{cases}, i=1, \dots, N_P \text{ and } j=1, \dots, D. \quad (15)$$

where $x_{j,i}^{\min}$ and $x_{j,i}^{\max}$ are the lower and upper bounds of the j^{th} decision parameter, respectively.

In the fitness evaluation, penalty functions can be used whenever there are violations to some equality and/or inequality constraints [8]. Basically, the objective function is substituted by a fitness function F_T that penalizes the fitness whenever the solution contains parameters that violate the problem constraints. The extended objective function (fitness function) can be defined as:

$$F_T = \sum_{i=1}^{ng} F_i + K \left| \sum_{i=1}^{ng} P_i - P_L - P_D \right|, \quad (16)$$

where K is the penalty factor of the equality constraint

Adaptive Differential Evolution Algorithm

As presented above, In DE, the fitness of an offspring is one-to-one competed with that of the corresponding parent. This one-to-one competition makes convergence speed of DE faster than other evolutionary algorithms. Nevertheless, this faster convergence property yields in a higher probability of searching toward a local optimum or getting premature convergence [9, 10].

The original DE uses a fixed positive values for the scaling factor F and the crossover constant C_R . This has an effect of restricting the exploration of the solution space, leading to a premature convergence. Thus, the optimal selection of these control parameters is very important in the success of the algorithm, as different parameter settings may lead to different results.

In this study, a new strategy in the selection of the parameter settings of DE algorithm is proposed. The basic idea is the development of an adaptive differential evolution algorithm, where the parameter of mutation and crossover is evolved rather than being fixed throughout the optimization process. The adaptation strategy is carried out by integrating the scaling factor F and crossover constant C_R in the population. This strategy explores effectively the solution space, maintains the exploratory feature and at the same time expedites the convergence.

Simulation Results

To illustrate the performance of the proposed adaptive differential evolution (ADE) approach, experiments are performed on the 6-unit power system, which considers the prohibited operating zones, ramp rate limits, and transmission network losses. This system contains six thermal units, 26 buses, and 46 transmission lines [11]. The required power demand to be met by all the six generating units is 1263 MW. Input data are shown in Table 1 and the loss coefficients with the 100-Mva base capacity are given bellow [11].

Simulations were carried out using MATLAB computational environment, on an Intel

Core2 Duo 2.10 GHz Laptop computer with 3 GB RAM under Windows 7.

Table 1. Data of the 6-unit system

Unit	P_i^{\min} (MW)	P_i^{\max} (MW)	c_i (\$)	b_i (\$/MWh)	a_i (\$/MW ² h)	P_i^0 (MW)	UR_i (MW/h)	DR_i (MW/h)	Prohibited zones (MW)
1	100	500	240	7.0	0.0070	440	80	120	[210–240] [350–380]
2	50	200	200	10.0	0.0095	170	50	90	[90–110] [140–160]
3	80	300	220	8.5	0.0090	200	65	100	[150–170] [210–240]
4	50	150	200	11.0	0.0090	150	50	90	[80–90] [110–120]
5	50	200	220	10.5	0.0080	190	50	90	[90–110] [140–150]
6	50	120	190	12.0	0.0075	110	50	90	[75–85] [100–105]

$$B_{ij} = 10^{-3} \begin{bmatrix} 1.7 & 1.2 & 0.7 & -0.1 & -0.5 & -0.2 \\ 1.2 & 1.4 & 0.9 & 0.1 & -0.6 & -0.1 \\ 0.7 & 0.9 & 3.1 & 0.0 & -1.0 & -0.6 \\ -0.1 & 0.1 & 0.0 & 2.4 & -0.6 & -0.8 \\ -0.5 & -0.6 & -1.0 & -0.6 & 12.9 & -0.2 \\ -0.2 & -0.1 & -0.6 & -0.8 & -0.2 & 15.0 \end{bmatrix} \quad (17)$$

$$B_{i0} = 10^{-3} [-0.3908 \quad -0.1297 \quad 0.7047 \quad 0.0591 \quad 0.2161 \quad -0.6635] \quad (18)$$

$$B_{00} = 0.0056 \quad (19)$$

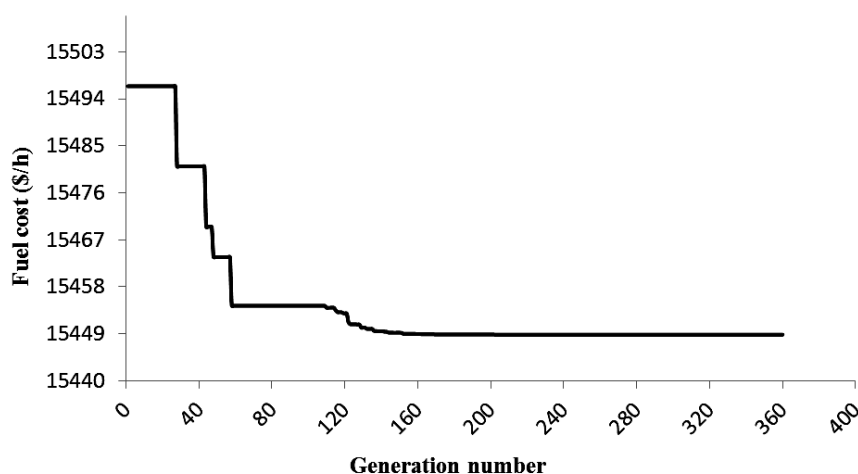
In order to demonstrate the efficiency and robustness of the proposed algorithm, 100 independent runs were performed using the control parameter settings listed in Table 2.

The average cost found by ADE was 15449.34 \$/h with a minimum cost of 15448.82 \$/h, and a maximum cost of 15462.89 \$/h (0.09% difference). The average execution time of the ADE for this test system is 1.01 s, which is very acceptable computation time for ELD solution. Also, it is important to point out that for all the trial runs, the convergence was reached without any violation of the generator constraints.

Table 3 presents a summary of the optimization results for the solution with minimum cost, which converged after 360 generations and 1.11 s. It is clear that the best solution obtained by ADE satisfies the system constraints such as the ramp rate limits and prohibited operating zones. The convergence of ADE for the trial run that produced the minimum cost solution is shown in Fig. 1.

Table 2. Control parameter settings of ADE algorithm

Parameter	Setting
Population size (N_p)	30
Maximum number of generations (G^{\max})	500
Scaling factor range F	[0.5 – 1.0]
Probability of crossover range (C_R)	[0.5 – 1.0]
Penalty factor (K)	6×10^5

*Figure 1. Convergence of the best solution found with ADE*

The best economic dispatch solution of the proposed approach were compared in Table 3 to those reported using particle swarm optimization (PSO) [11], genetic algorithm (GA) [11], adaptive particle swarm optimization (APSO) [12], binary successive approximation based evolutionary search (BSA-EV) [13], distributed sobol PSO with tabu search algorithm (DSPSO-TSA) [14] and differential evolution (DE) [15].

From Table 3, it is obvious that ADE is superior to the original differential algorithm (DE) with regard to the solution quality. It can be seen also that the results given by ADE are better than those reported in the literature, except for the solutions of APSO, BSA-EV and DSPSO-TSA reported in Panigrahi [12], Dhillon [13] and Khamsawang [15], respectively, which are less expensive. However, it is important to note that in the cases of the APSO, BSA-EV and DSPSO-TSA methods, the power balance constraint (6) is not satisfied. Indeed, by using the loss formula (7), the actual transmission losses obtained from the depicted generation schedules of APSO, BSA-EV and DSPSO-TSA, are: 12.862 MW, 12.981 MW and

13.148 MW, respectively. The errors in the power balance constraint of these three last methods are provided in Table 4, which shows that the error of ADE is tolerable (0.08 MW) and is the lowest compared with those of APSO, BSA-EV and DSPSO-TSA. As a conclusion, we can say that the proposed ADE approach has the ability to find the best accurate economic dispatch solutions compared to those obtained with recent heuristic approaches.

Table 3. Comparison of the best solution obtained by ADE

Power output (MW)	PSO [11]	GA [11]	APSO [12]	BSA-EV [13]	DSPSO-TSA [14]	DE [15]	Proposed ADE
P1	447.497	474.807	446.669	456.680	439.293	447.744	447.486
P2	173.322	178.636	173.156	170.676	187.788	173.407	173.307
P3	263.474	262.209	262.826	265.000	261.026	263.411	263.450
P4	139.059	134.283	143.469	136.540	129.497	139.076	139.056
P5	165.476	151.904	163.914	161.852	171.710	165.364	165.455
P6	87.128	74.181	85.344	84.728	86.165	86.944	87.123
Total power (MW)	1276.010	1276.030	1275.376	1275.477	1275.514	1275.947	1275.877
Loss (MW)	12.958	13.022	^a (12.862)	^a (12.981)	^a (13.148)	12.957	12.957
Total cost (\$/h)	15450.00	15459.00	15444.00	15444.01	^b (15444.61)	15449.77	15448.82

^a Represents the actual transmission loss as per given generation schedule.

^b Denotes the exact fuel cost obtained from the above schedule.

Table 4. Errors engendered by APSO, BSA-EV, DSPSO-TSA and ADE methods

	APSO [12]	BSA-EV [13]	DSPSO-TSA [15]	ADE
Error in MW ($\sum P_i - P_D - P_L$)	0.49	0.50	0.63	0.08

Table 5 presents the minimum, average and maximum costs of 100 trials for ADE, which are compared with other heuristic techniques available in the literature. From this Table, we can see that ADE gives the best average cost with reference to the satisfaction of the energy balance constraint. It is noted that the execution times of the DEPSO are not compared with that of the other techniques, since the solution times of each method are measured on a different hardware.

The statistical results of 100 runs by ADE with 100 different initial trial solutions are depicted in Fig. 2. This figure shows that 91% of the solutions are within 0.005% of the minimum cost (15448.82 \$/h), indicating a good convergence characteristic. It can be concluded that ADE algorithm is robust and effective in solving the ELD problem

considering practical generator operation constraints, such as prohibited operating zones and ramp rate limits.

Table 5. Comparison of simulation results

Method	Minimum cost (\$/h)	Average cost (\$/h)	Maximum cost (\$/h)
PSO [11]	15450.00	15454.00	15492.00
GA [11]	15459.00	15469.00	15524.00
APSO [12]	15443.58	15449.99	NA
BSA-EV [13]	15444.01	NA	NA
DSPSO-TSA [14]	15441.57 *(15444.61)	15443.84	15446.22
DE [15]	15449.77	15449.78	15449.87
Proposed ADE	15448.82	15449.34	15462.89

Note: NA, Not available.

* Denotes the exact fuel cost obtained from the best schedule reported in [14].

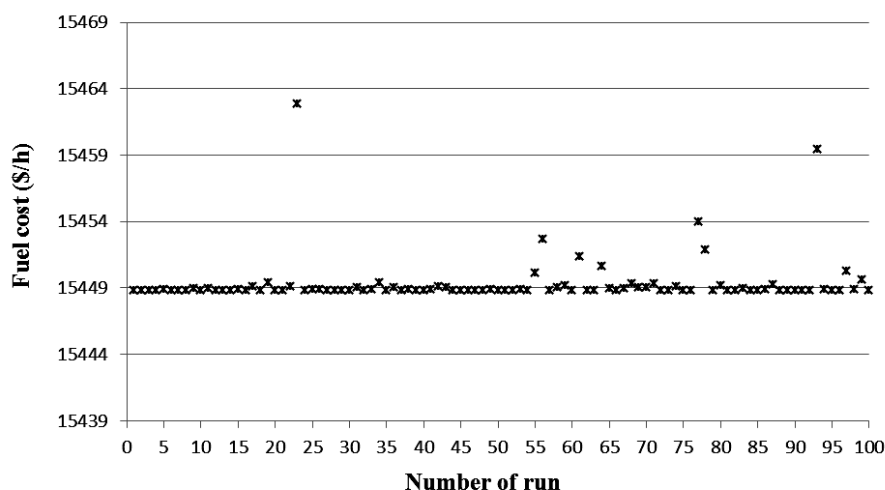


Figure 2. Distribution of fuel cost achieved by ADE

Conclusion

In this study, an efficient approach based on the adaptive differential evolution (ADE) algorithm was developed and successfully applied to solve the economic load dispatch problem with taking into account nonlinear generator features such as ramp rate limits and prohibited operating zones. A dynamic mutation and crossover parameters are suggested in

order to improve the global and local search abilities of the proposed ADE.

The feasibility of the proposed ADE was demonstrated on the 6-unit benchmark test system. Simulation results have demonstrated that the proposed improvement was a powerful strategy to prevent premature convergence to local minima, providing high quality solutions. Also, ADE algorithm has shown superior features such as accurate solution, stable convergence characteristic, and good computation efficiency, compared to other heuristics reported in the literature recently.

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