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Modified Differential Evolution for Multi-objective Load Dispatch Problem Considering Quadratic Fuel Cost Function

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Abstract

This paper proposes a Modified Differential Evolution (MDE) for solving multi-objective load dispatch (MOLD) problem where transmission power losses are considered. MDE is an improved version of conventional Differential Evolution (CDE) in which the mutation operation of the CDE is improved by using five differential solutions instead of three ones similar to CDE. In the MOLD problem, three cases of dispatch including economic dispatch, emission dispatch and multi-objective dispatch are carried out by considering fuel cost function, emission function and both fuel cost and emission functions. In the third case of dispatch, there is a price penalty factor employed to determine the best compromise solution instead of using Fuzzy-based mechanism similar to other studies. The performance of MDE is verified by testing on two systems with three units and one system with six units. In the two systems, the fuel cost and emission from MDE are compared to those from CDE and other existing meta-heuristic algorithms, and the analysis on the result comparison indicates that the MDE is a promising algorithm for solving the MOLD problem.

Keywords: *Modified differential evolution, multi-objective, economic dispatch, emission dispatch*

Nomenclature

F_{1i}	Fuel Cost function of thermal unit i in \$/h
F_{2i}	Emission function of thermal unit i in kg/h
w_1, w_2	Weights corresponding to the fuel cost and emission objectives.
a_i, b_i, c_i, e_i, f_i	Fuel cost coefficients of thermal plant i;
α_i, β_i, γ_i	Emission coefficients of thermal unit i.
N	Number of thermal units
P_D	Load demand of the system in MW
P_L	Total network loss of the system in MW
P_i	Output power of unit i in MW
B_{ij}, B_{0i}, B_{00}	Transmission loss formula coefficients
P_{imin}, P_{imax}	Lower and upper generation limits of unit i in MW
$rand$	Uniformly distributed random number in [0, 1]
P_{1d}	Power output of the slack thermal unit 1 of nest d in MW

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P_{1max}, P_{1min}	Maximum and minimum power outputs of slack thermal unit 1 in MW
$P_s^{\lim}$	Limit for the slack unit 1 in MW
PR	The price penalty factor.
F	Mutation factor
CR	Crossover factor
NP	Number of population

1. Introduction

Multi-objective load dispatch is a very important problem in power system since both electricity generation fuel cost and emission produced from the electricity generation process are minimized in addition to satisfying power balance constraint and all thermal unit constraints such as maximum and minimum limits on power output

Recent decades, many methods based on deterministic algorithms and meta-heuristic algorithms have been widely and successfully applied for solving the MOLD problem such as lambda-iteration method [1], Hopfield Lagrange Network (HNN) [1], Improved Hopfield Neural Network Model (IHNN) [2], Tabu Search (TS) [3], fuzzy logic controlled genetic algorithm (FCGA) [4], the Non-dominated Sorting Genetic Algorithm - II (NSGA-II) [5], Differential Evolution (DE) [6], biogeography-based optimization (BBO) [7], multi-objective differential evolution (MODE) [8], Hybrid Differential volution-sequential quadratic programming (DE-SQP) and Hybrid Particle Swarm optimization- sequential quadratic programming (PSO-SQP) [9], parallel synchronous PSO algorithm (PSPSO) [10], Basic Cuckoo Search Algorithm (BCSA) [11].

Among the methods, Lambda-iteration and HNN are ones based on the Lagrange optimization function where the comer is mainly dependent on the initial value of lambda which is predetermined and the increased value of lamda whereas the later must suffer difficulty of determining control parameters. It is stated from the study [1] that the application of the methods is easy due to the simple implementation for the problem. The HNN copes with the local optimization with high number of iteration for convergence and long execution time. The mentioned methods have the same characteristic that they cannot deal with the problem where nonconvex objective function is considered. On the contrary, methods belonging to meta-heuristic algorithms such as DE, MODE, PSPSO and CSA, *etc.*, can tackle the drawback since they simply obtain optimal solution for large scale system with nonconvex objective function. The difference between DE and MODE is that MODE can determine the best compromise solution, which can satisfy both cost, and emission minimization requirement without using fuzzy mechanism like DE. The advantage allows MODE to reduce the computing procedure and execution time as well.

Recent years, methods formed by combining two original algorithms have widely been developed for solving MOLD problem such as DE-SQP and PSO-SQP. The advantage of the methods is that they can take advantage of each individual to enhance the solution approaching the global optimization; however, the methods have to cope with the selection of higher number of control parameters and longer execution time.

Differential evolution (DE) [12], one of the most popular and widely applied algorithms, was also developed based on a population by Storn and Price in 1995. The DE has been successfully applied for solving optimization problems so far in electrical engineering fields such as economic load dispatch [13-15]. However, the conventional DE has been considered less effective for systems where complicated objective functions such as nonconvex function are taken into account since the vale point loading effects of thermal unit are included. Consequently, the modified version of the CDE has been developed to improve its performance.

In this paper, the performance of MDE has been validated by testing on different test systems with diversity of constraints. Namely, the power losses on transmission lines are taken into consideration. The obtained results in terms of fuel cost, emission and execution time from MDE are compared to other methods consisting of CDE, Tabu Search (TS) [3], FCGA [4] and CGA [4], [NSGA-II [5], BBO [7], and CSA [11].

2. Problem Formulation

2.1. Fuel Cost Objective

The most simplified fuel cost function $F_1(P_i)$ for thermal unit i loaded with P_i MW is approximated by a quadratic function. However, it is more practical to consider valve point loading effects on the fuel cost function of thermal units where the fuel cost curve of thermal units contains higher order of nonlinearity and discontinuity. Therefore, the fuel cost function can be accurately modeled in terms of real power output as a non-smooth cost function as follows [16]:

$$F_{1i} = a_i + b_i P_i + c_i P_i^2 + \left| e_i \times \sin\left(f_i \times \left(P_i^{\min} - P_i \right) \right) \right| \tag{1}$$

2.2. Emission Objective

In the classical economic load dispatch problem, the fuel cost of thermal units is usually the main objective since the emission released into the air from thermal units is neglected. However, the amount of emission from the fossil fuel fired thermal plants is a major cause increasing the earth temperature and environment pollution level. Therefore, the emission produced by thermal units can be expressed in form of a quadratic function as follows [17]:

$$F_{2i} = \alpha_i + \beta_i P_i + \gamma_i P_i^2 \tag{2}$$

2.3. Combined Economic and Emission Objective

The economic dispatch and emission dispatch are optimization problems where the emission objective is neglected in the economic dispatch problem and the fuel cost objective is not considered in the emission dispatch problem. However, there is a conflict between the two objectives. It means that as the fuel cost is minimized, the emission can increase and vice versa. Therefore, the compromise solution for the bi-objective problem needs to be determined. There have been two methods to be employed for dealing with the issue so far including a fuzzy based mechanism [1, 7, 11] and the price penalty factor based method [18-19]. In this paper, the bi-objective optimization problem is converted to a single objective one using a price penalty factor based method as follows.

$$\text{Minimize} \quad TC = w_1 \times F_{1i}\left(P_i\right) + w_2 \times \mathrm{PR} \times F_{2i}\left(P_i\right) \tag{3}$$

There are three dispatch cases including economic dispatch ($w_1=1$, $w_2=0$), emission dispatch ($w_1=0$, $w_2=1/PR$) and multi-objective dispatch ($w_1=1$, $w_2=1$). The following steps are applied to determine the price penalty factor PR for a particular load over optimal interval [20].

Step 1: Calculate the average fuel cost for each MW of each thermal unit at full generation.

Step 2: Calculate the average emission for each MW of each thermal unit at full generation.

Step 3: Calculate the ratio of the average cost to average emission for each thermal unit and thus PR_i is obtained by

$$PR_i = \frac{F_1(P_{i\max})/P_{i\max}}{F_2(P_{i\max})/P_{i\max}} \ (\$/lb) \tag{4}$$

Step 4: Arrange the price penalty factor in ascending value order

Step 5: Sum the maximum capacity of each unit ($P_{i,max}$) beginning from the full generation of thermal units with the lowest value of the factor until the sum is equal or higher than the load demand.

Step 6: At this stage, the price penalty factor *PR* associated with the final unit in the process is chosen as the price penalty factor.

The values of the factor obtained in [20] have shown that *PR* depends on the load demand and note that there is only one value of the factor.

On the other hands, all variables in eq. (1) must satisfy all the equality and inequality constraints below.

1. Real Power balance constraints: the total power generated by all thermal units must be equal to the sum of load demand and transmission losses.

$$\sum_{i=1}^{N} P_i - P_L - P_D = 0 \tag{5}$$

Where the transmission line power losses P_L is determined by:

$$P_L = \sum_{i=1}^{N_1} \sum_{j=1}^{N_1} P_i B_{ij} P_j + \sum_{i=1}^{N} B_{0i} P_i + B_{00} \tag{6}$$

2. Generator operating limits: power output of thermal unit must be in feasible operating zone.

$$P_{i\min} \le P_i \le P_{i\max} \tag{7}$$

3. Modified Differential Evolution for MOLD Problem

3.1. Conventional Differential Evolution

Differential evolution (DE) [7], one of the most popular and widely applied algorithms, was also developed based on a population by Storn and Price in 1995. The search process for optimal solution of the DE is different from PSO. In fact, the PSO finds out optimal solution inspiring from the behavior of the fish or bird whereas the DE is mainly based on the evolutionary on humanity with three important phases such as mutation, crossover and selection. However, CDE also performs one new solution generation at each iteration similar to PSO. A brief description of the DE is as follows:

3.1.1. Initialization

At the beginning, a population is arbitrarily randomized within its limitations as below:

$$X_i^j = X_{\min}^j + rand * (X_{\max}^j - X_{\min}^j) \tag{8}$$

where $X_{\max}^j$, $X_{\min}^j$ are the upper and lower bounds, respectively, of the *jth* variable of the given problem; X_i^j is the *jth* control variable of the *ith* target vector; *rand* is a uniformly distributed random number between 0 and 1.

3.1.2. Mutation

Mutation is the first new solution generation via generation of offspring. The operation of mutation is applied.The mutation operation creates mutant vectors by perturbing a randomly selected vector with the difference of two other randomly selected vectors as per following equation.

$$Y_i^G = X_a^G + F * (X_b^G - X_c^G) \tag{9}$$

where X_a^G, X_b^G, X_c^G are three target vectors chosen randomly from the current population; F is a positive control parameter used for scaling the difference vector.

3.1.3. Crossover

Crossover represents a typical case of a 'genes' exchange. The parent vector is mixed with the mutated vector to create a trial vector, according to the following equation:

$$Z_i^G = \begin{cases} Y_i^G & if \quad rand_2 \le CR \\ X_i^G & otherwise \end{cases} \tag{10}$$

3.1.4. Selection

Selection procedure is used among the set of trial vector and the updated target vector to choose the best. Each solution in the population has the same chance of being selected as parents. Selection is carried out by comparing the objective function values of target vector and trial vector. For minimization problem, if the trial vector has better value of the objective function, then it replaces the updated one as per. The selection operation may mathematically be expressed as follows:

$$X_i(G+1) = \begin{cases} Z_i(G) & if \quad f[Z_i(G)] \le f[X_i(G)] \\ X_i(G) & otherwise \end{cases} \tag{11}$$

This optimization process is repeated for serveral iterations allowing individuals to improve their fitness as they explore the solution space in search for optimal solutions.

3.2. Modified Differential Evolution.

In the proposed MDE, the new solutions generated by mutation operation are improved by evaluating the fitness function.

The method for produce a new solution d is determined as follows:

$$Y_d^G = X_a^G + F * (X_b^G - X_c^G + X_e^G - X_f^G) \tag{12}$$

where $X_a^G, X_b^G, X_c^G, X_e^G, X_f^G$ are five target vectors chosen randomly from the current population.

3.3. Implementation of MDE for MOLD problem

The main steps for the proposed MDE for solving MOLD problem are described as follows:

1) *Initialization:* Similar to other meta-heuristic algorithm, in the MDE each solution

in the population Np is represented by a vector X_d = $[P_{d2}, \ldots\ldots, P_{dN}]$ $(d = 1, \ldots, N_p)$. The maximum and minimum values of each solution are respectively $X_{min}=[P_{imin}]$ and $X_{max}=[P_{imax}]$. Consequently, each solution X_d is randomly initialized within the limits $X_{min} \leq X_d \leq X_{max}$ $(i=2, \ldots, N)$ as follows:

$$X_d = X_{\min} + rand * (X_{\max} - X_{\min}) \tag{13}$$

The power output of from thermal unit 2 to thermal unit N is available, the thermal unit 1 P_{d1} for each solution d is then obtained by using the eq. (4) and (5).

$$P_{1d} = \sum_{i=2}^{N} P_{id} - P_L - P_D \tag{14}$$

Fitness function is calculated to evaluate the quality of each solution. The value includes objective function value and the penalty value of the slack thermal unit 1. The detail of fitness function is as below

$$FT_d = \sum_{i=1}^{N} \left[w_1 \times F_1(P_i) + w_2 \times \mathrm{PR} \times F_2(P_i) \right] + K_s (P_{1d} - P_{1d}^{\lim})^2 \tag{15}$$

where the limit in (15) is obtained by:

$$P_1^{\lim} = \begin{cases} P_{1\max} & if\ P_{1d} > P_{1\max} \\ P_{1\min} & if\ P_{1d} < P_{1\min} \\ P_{1d} & \text{otherwise} \end{cases} \tag{16}$$

2) Newly generated solutions by using mutation operation

New solutions are then generated using eq. (12). There is not criterion to assure that the new solutions are always exactly met their limit constraints. Therefore, the redefinition of the new solutions is carried out as follows:

$$X_d^{new} = \begin{cases} X_{d\max} & \text{if} \quad X_d^{new} > X_{d\max} \\ X_{d\min} & \text{if} \quad X_d^{new} < X_{d\min} \\ X_d^{new} & otherwise \end{cases} \tag{17}$$

3) Crossover operation

In order to generate new solutions for the next iteration, there must be a mixture between the current solutions and the previous iteration's solutions. Consequently, the crossover operation as described in Section 3.1.3 is performed.

4) Selection operation

The selection operation is carried out to keep the better solutions until the current iteration. The best solution with the lowest fitness function value is then determined based on the evaluation of the fitness function.

5) Stopping criteria

The computing process is terminated when the current iteration is equal to the predetermined maximum number of iterations.

3.3. Overall Iterative Algorithm

The overall procedure of the proposed MDE for solving the MOLD problem is described as follows:

Step 1: Select values for control parameters N_p, G_{max}, F and CR.
Step 2: Initialize a population as in eq. (13) and calculate the slack unit using eq. (14).
Step 3: Calculate fitness function (15) and set the iteration counter $G = 1$.
Step 4: Generate new solutions using mutation operation as in Section 3.1.2.
Step 5: Fix invalid solutions using eq. (17)
Step 6: Calculate slack unit 1 and the fitness function
Step 7: Perform crossover operation as in Section 3.1.3
Step 8: Perform selection operation as in Section 3.1.4
Step9: If the current iteration $G < G_{max}$, $G = G + 1$ and return to Step 4. Otherwise, determine the best solution with the lowest fitness function and stop the procedure.

4. Results and Discussions

To validate the efficiency of the proposed MDE, two systems with quadratic fuel cost and emission function are employed. Furthermore, the conventional Differential Evolution (CDE) is also implemented for the two systems to compare the performance between MDE with CDE. In the systems, the first one is comprised of three thermal units with transmission line power losses [5] and the second consists of six units with 800 MW load [4-5]. All methods are run twenty independent trials for each case of a set control parameter in Matlab 7.2 programming language and on a 1.8 GHz PC with 4 GB of Ram.

4.1. System I with three thermal units

To implement CDE and MDE for the system, the population and the maximum number of iteration are respectively set to 10 and 50 while other control parameters consisting of CR and F are respectively set to the range of [0.2; 0.8] and [0.2; 1.2] with a step of 0.2.

Case 1: Economic dispatch ($w_1 = 1$, $w_2 = 0$)

In this case, the problem is regarded as a pure economic load dispatch problem considering only the fuel cost objective. The summary of the results given in Tables 1 and 2 including minimum total cost, average total cost, maximum total cost, standard deviation cost and average computational time indicate that the best solution for minimum, average, maximum and standard deviation emissions from MDE are mostly less than those from CDE at the same values of control parameters. Figure 1 shows the fuel cost convergence characteristic obtained by CDE and MDE. Obviously, MDE finds better solution than CDE since the number of current iterations is higher than 17.

Case 2: Emission dispatch ($w_1 = 0$, $w_2 = 1/PR$)

The pollutant emission is only considered in objective function for this case. Therefore, it is a pure emission dispatch problem. The obtained results comparison given in Table 3 points out that the MDE is more efficient than CDE due to less minimum emission, less average emission, less maximum emission and less standard deviation. The emission convergence characteristic from CDE and MDE is depicted in Figure 2. Dissimilar to Figure 1, the solution from MDE is better than CDE at each iteration in the whole search process.

Case 3: Combined economic and emission dispatch ($w_1=1$, $w_2=1$ *and PR*)

This case considers the problem with two objectives minimizing both fuel cost and emission. Similar to Cases 1 and 2, the best optimal solution is searched in the range of two control parameters, CR and F. There is a set of solutions found out and the best solution is then determined by comparing the fuel cost and emission.

The comparison of result obtained by CDE, MDE and other methods including Tabu Search (TS) [3], FCGA [4] and CGA [4], [NSGA-II [5], BBO [7], and CSA [11] are reported in Table 4. Clearly, the MDE sobtains approximate or better solution than other method because it obtains the equal or less fuel cost and emission. In addition, the MDE is slower than CSA. Other methods have not reported their execution time. Optimal solutions for the three dispatch cases are shown in Table 5.

Table 1. Obtained Results for Economic Load Dispatch of System 1 with CR from 0.2 to 0.4

CR	F	Method	Min.	Average cost ($/h)	Max. cost($/h)	Std. dev. ($/h)	CPU time (s)
0.2	0.2	CDE	8344.6116	8345.513	8347.313	2.2768	0.1734
		MDE	8344.5968	8345.002	8346.795	0.0364	0.1672
	0.4	CDE	8344.5946	8345.285	8347.272	1.3452	0.1578
		MDE	8344.6122	8344.738	8344.866	0.1441	0.1578
	0.6	CDE	8344.6012	8344.98	8346.131	1.1976	0.1578
		MDE	8344.607	8345.016	8346.09	1.0716	0.1594
	0.8	CDE	8344.6253	8345.806	8351.354	3.7334	0.1578
		MDE	8344.5937	8345.012	8346.413	4.43	0.1547
	1	CDE	8344.707	8346.139	8347.884	2.7864	0.1578
		MDE	8344.6101	8344.985	8345.861	0.7726	0.1531
	1.2	CDE	8344.7698	8345.925	8348.064	3.5337	0.1609
		MDE	8344.7282	8345.426	8346.985	0.2472	0.1609
0.4	0.2	CDE	8344.6042	8345.039	8345.794	0.4131	0.1594
		MDE	8344.5947	8344.623	8344.785	0.5142	0.1594
	0.4	CDE	8344.5972	8344.614	8344.624	0.0339	0.1594
		MDE	8344.5935	8344.608	8344.625	0.0368	0.1672
	0.6	CDE	8344.6004	8344.611	8344.624	0.0333	0.1594
		MDE	8344.5969	8344.631	8344.816	0.0379	0.1625
	0.8	CDE	8344.5956	8344.711	8344.957	0.0454	0.1625
		MDE	8344.5936	8344.678	8344.859	0.5715	0.1594
	1	CDE	8344.5987	8345.096	8346.322	0.5461	0.175
		MDE	8344.6202	8345.213	8346.7	0.4533	0.1703
	1.2	CDE	8344.5978	8344.921	8345.87	0.7592	0.175
		MDE	8344.6428	8345.38	8346.619	1.7579	0.175

Table 2. Obtained Results for Economic Load Dispatch of System 1 with CR from 0.6 to 1

CR	F	Method	Min.	Average cost ($/h)	Max. cost($/h)	Std. dev. ($/h)	CPU time (s)
0.6	0.2	CDE	8344.616	8346.559	8358.807	3.1639	0.1719
		MDE	8344.5948	8344.605	8344.618	0.0024	0.1688
	0.4	CDE	8344.597	8344.866	8347.009	0.8443	0.175
		MDE	8344.5937	8344.602	8344.616	0.0221	0.1672
	0.6	CDE	8344.5951	8344.606	8344.619	0.0049	0.1719
		MDE	8344.5927	8344.606	8344.623	0.0025	0.1688
	0.8	CDE	8344.5962	8344.609	8344.622	0.0135	0.1734
		MDE	8344.594	8344.602	8344.617	0.0349	0.1703
	1	CDE	8344.595	8344.688	8344.859	0.1113	0.175
		MDE	8344.6091	8345.051	8345.972	2.9104	0.1766
	1.2	CDE	8344.5945	8344.714	8344.958	0.379	0.175
		MDE	8344.6085	8345.176	8347.377	1.2497	0.1672
0.8	0.2	CDE	8344.6073	8345.556	8347.551	4.4783	0.1766
		MDE	8344.5942	8344.604	8344.62	0.0141	0.1719
	0.4	CDE	8344.5957	8344.602	8344.611	0.013	0.1766
		MDE	8344.5952	8344.606	8344.622	0.0208	0.1703
	0.6	CDE	8344.5930	8344.598	8344.613	0.002	0.1719
		MDE	8344.5929	8344.605	8344.622	0.0531	0.1703
	0.8	CDE	8344.5931	8344.613	8344.624	0.0098	0.1734
		MDE	8344.5965	8344.625	8344.764	0.0395	0.1641
	1	CDE	8344.5936	8344.629	8344.783	0.1085	0.1719
		MDE	8344.5941	8344.674	8344.824	0.473	0.1641
	1.2	CDE	8344.6016	8344.643	8344.936	0.1	0.1766
		MDE	8344.5933	8344.862	8345.56	0.7235	0.1625
1	0.2	CDE	8344.6137	8346.233	8350.999	2.2829	0.1781
		MDE	8344.5953	8344.62	8344.734	0.0487	0.1625
	0.4	CDE	8344.5971	8344.745	8345.538	0.465	0.175
		MDE	8344.5941	8344.606	8344.623	0.0332	0.1656
	0.6	CDE	8344.5930	8344.602	8344.623	0.0251	0.1734
		MDE	8344.593	8344.608	8344.623	0.0392	0.1641
	0.8	CDE	8344.5984	8344.609	8344.622	0.0214	0.1641
		MDE	8344.5942	8344.607	8344.621	0.0011	0.1594
	1	CDE	8344.602	8344.751	8345.112	0.4709	0.1594
		MDE	8344.5967	8344.61	8344.623	0.0073	0.1625
	1.2	CDE	8344.597	8344.61	8344.65	0.0071	0.1594
		MDE	8344.621	8344.767	8344.903	0.1428	0.1594

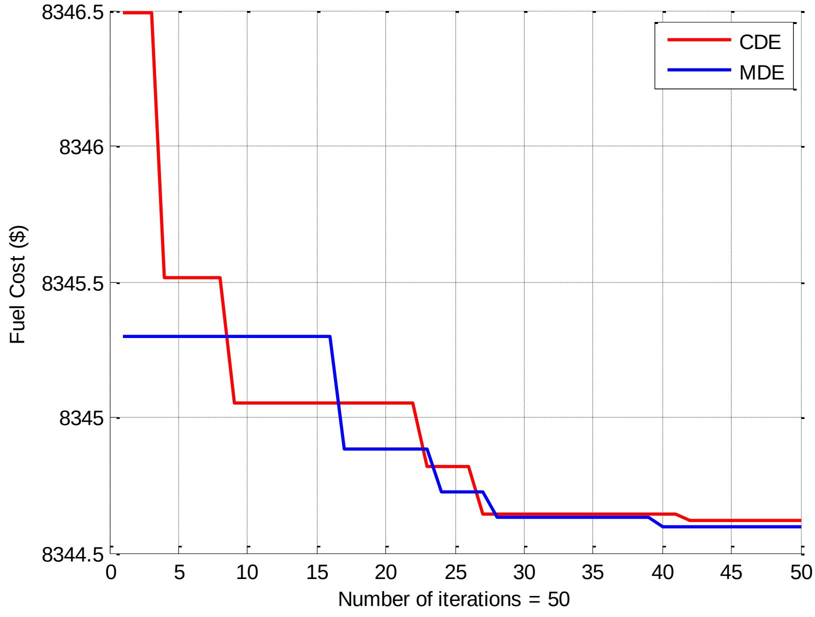

Figure 1. The Fitness Convergence Characteristic for Economic Dispatch

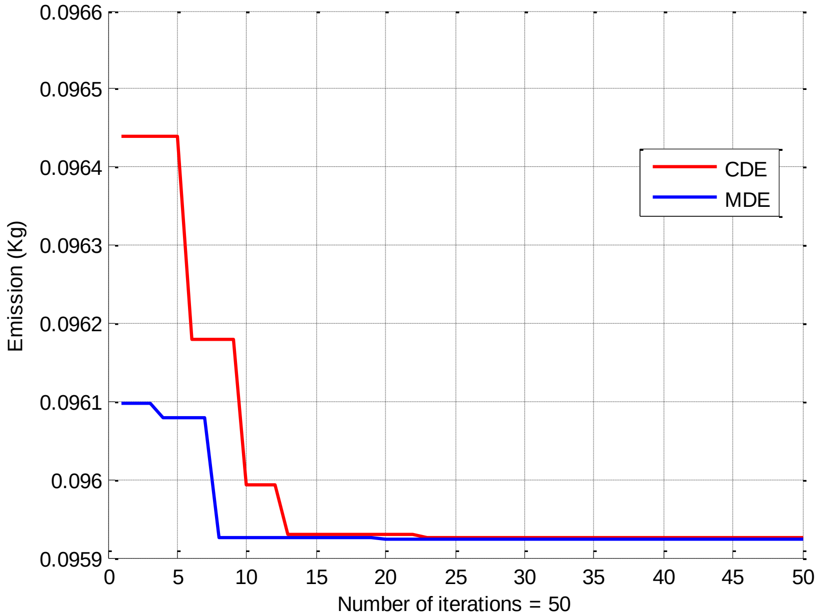

Figure 2. The Fitness Convergence Characteristic for Emission Dispatch

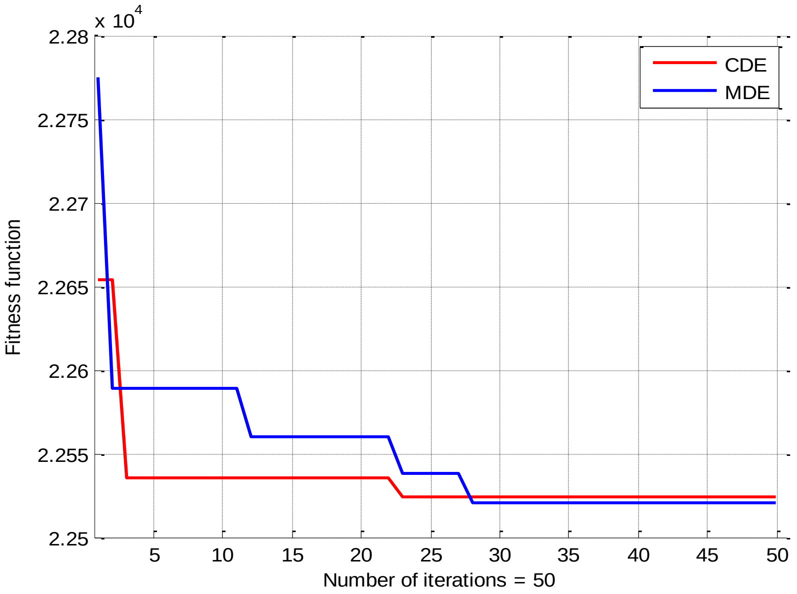

Figure 3. The Fitness Convergence Characteristic for Economic Dispatch

Table 3. Obtained Results for Emission Dispatch and Combined Economic Emission Dispatch for System 1

Case	*Method*	Min. cost ($/h)	Average cost ($/h)	Max. cost($/h)	Std. dev. ($/h)	CPU time (s)
Emission dispatch	CDE	0.0959241	0.0959341	0.0959512	0.00012	0.16
	MDE	0.0959239	0.0959239	0.0959239	0	0.16

Table 4. Result Comparisons for System 1

Dispatch	Method	Tabu Search [3]	NSGA-II [5]	BBO [7]	CSA [11]	CDE	MDE
Economic dispatch	Cost ($/h)	8344.60	8344.60	8344.59	8344.59	8344.5930	8344.5927
	Cpu (s)	-	-	-	0.09		
Emission dispatch	Emission (kg/h)	0.0958	0.09593	0.09592	0.09592	0.0959241	0.0959239
	Cpu (s)	-	-	-	0.07	0.16	0.16
Economic emission dispatch	Cost ($/h)	-	8349.72		8349.722	8362.8463	8360.5671
	Emission (kg/h)	-	0.09654		0.09654	0.0959312	0.0959259
	Cpu (s)	-	-		0.09	0.15	0.14

Table 5. Optimal Generations obtained by MDE for System 1

Generation (MW)	Economic dispatch	Emission dispatch	Economic emission dispatch
P_1	435.2404	508.21	499.9248
P_2	299.8639	250.992	255.2092
P_3	130.7219	105.553	109.6689

4.2. System II with Six Thermal Units

Similar to the manners done in Section 4.1 for system 1, optimal solutions obtained by the MDE for the three dispatch cases for load of 800 MW are compared to those from other methods dedicated in Table 6. Obviously, the MDE obtains better cost than CGA and FCGA in [4] for economic dispatch and better both cost and emission than CDE for all cases. With respect to comparison with CSA, MDE has approximate cost and emission with CSA [11] for economic dispatch and emission dispatch but better cost and emission than CSA for the economic and emission dispatch.

On the other hand, the MDE is much robust than the CGA and FCGA because it spends much shorter time than these methods for searching optimal solutions. Although the MDE is slower than CSA; however, MDE is also a fast algorithm since the number of iterations and population are two small values of 100 and 10. Consequently, it is concluded that the MDE is very efficient for solving the bi-objective load dispatch. For convergence characteristic comparison plotted in Figures 4, 5 and 6, MDE clearly finds out better solution than CDE at almost iterations. The optimal generations for the system are given in Table 7.

Table 6. Result Comparisons for System 2 for 800 MW Load

Dispatch	Method	CGAs [4]	FCGAs [4]	CSA [11]	CDE	MDE
Economic dispatch	Cost ($/h)	8232.89	8231.03	8227.1	8227.6	8227.093
	Cpu (s)	14.46	5.62	0.031	0.16	0.16
Emission dispatch	Emission (kg/h)	-	-	526.3901	526.3908	526.3901
	Cpu (s)	-	-	0.03	0.17	0.16
Economic emission dispatch	Cost ($/h)	-	-	8269.5117	8293.5505	8267.2118
	Emission (kg/h)	-	-	568.8394	527.678	526.9213
	Cpu (s)	-	-	0.032	0.1	0.1

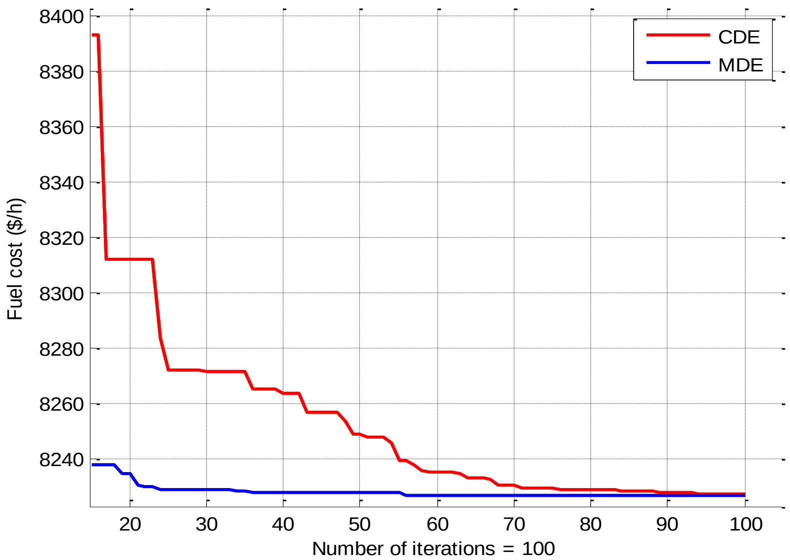

Figure 4. The Fitness Convergence Characteristic for Economic Dispatch

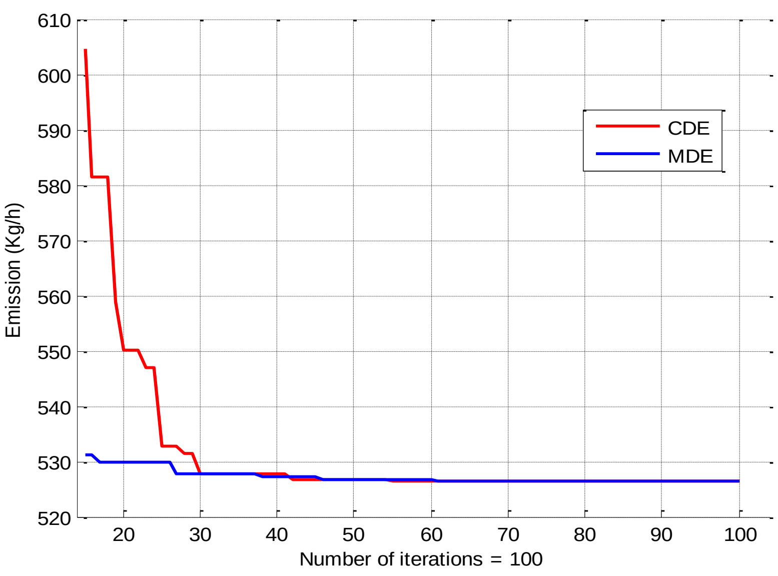

Figure 5. The Fitness Convergence Characteristic for Emission Dispatch

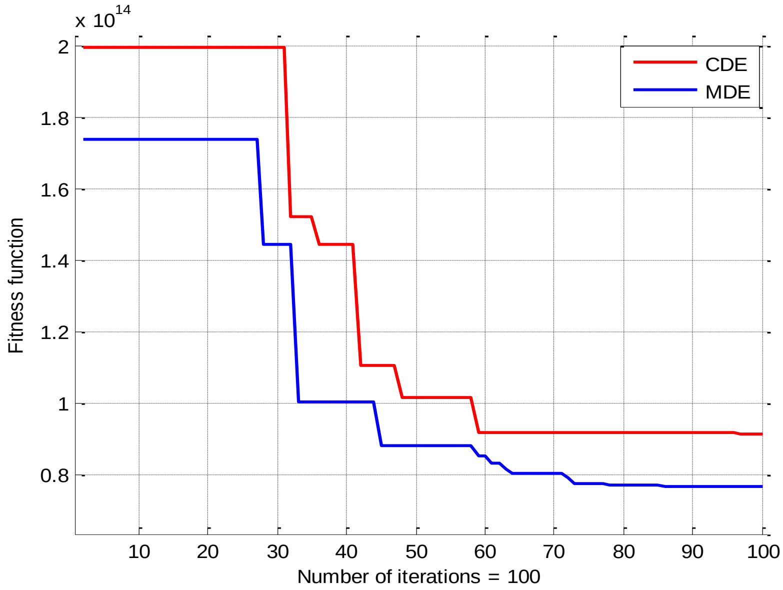

Figure 6. The Fitness Convergence Characteristic for Economic Emission Dispatch

Table 7. Optimal Solution obtained by MDE for Test System 2

Generation (MW)	Economic dispatch	Emission dispatch	Economic-emission dispatch
P_1	800	100.0022	102.7895
P_2	100	100	100
P_3	100	117.9727	113.0295
P_4	53.2197	140.0005	140
P_5	200.891	170.9199	169.9089
P_6	172.946	171.1047	174.272

5. Conclusion

In this paper, a Modified Differential Evolution has been successfully applied for solving bi-objective load dispatch problem. The method is an improved version of original DE in which the first new solutions via mutation operation is modified by using five random solutions instead of three ones. The performance of MDE is validated by testing on two systems with transmission line power losses is considered. The obtained result comparison have shown that MDE is very efficient as applied to the economic emission dispatch because it can obtain better solution and faster simulation time than others.

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