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Environmental Economic Hydrothermal System Dispatch by Using a Novel Differential Evolution

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Abstract. This paper proposes the Novel Differential Evolution (NDE) method for solving the environmental economic hydrothermal system dispatch (EEHTSD) problem with the aim to reduce electricity generation fuel costs and emissions of thermal units. The EEHTSD problem is constrained by limitations on generations, active power balance, and amount of available water. NDE applies two modified techniques. The first one is modified mutation, which is used to balance global and local search. The second one is modified selection, which is used to keep the best solutions. When performing this modified selection, the proposed method completely reduces the impact of crossover by setting it to one. Moreover, the task of tuning this factor can be canceled. Original Differential Evolution (ODE), ODE with the first modification (MMDE), and ODE with the second modification (MSDE), and NDE were tested on two different hydrothermal systems for comparison and evaluation purposes. The performance of NDE was also compared to existing methods. It was indicated that the proposed NDE is a very promising method for solving the EEHTSD problem.

Keywords: *available water constraints; emission function; fuel cost function; modified mutation; modified selection; nonconvex objective.*

1 Introduction

Hydrothermal systems are composed of thermal plants and hydropower plants that supply electricity load through transmission lines. For electricity generation, thermal power plants use expensive fossil fuels and release huge amounts of emissions into the air. Thus, the EEHTSD problem aims to minimize electricity generation fuel cost and emissions released from thermal plants while all constraints are satisified [1-5].

The EEHTSD problem has been widely and successfully applied so far by using different optimization algorithms. The simulated annealing-based goal-

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attainment (SA-BGA) method [3] has been implemented for fuel cost and emission dispatch but only some weight values were used. Therefore, the best emission was small but the best fuel cost was much higher than an appropriate value. Improved particle swarm optimization (IPSO) [4] has been proposed by using PSO and Lagrange optimization. This method can reduce a high number of control variables and shorten the search process. However, its application is stopped when nonconvex functions are employed. The Non-dominated Sorting Genetic Algorithm-II (NSGA-II) [5] has been proven to be effective and was compared to other methods such as the Real-coded Genetic Algorithm (RCGA) and Multi-objective Differential Evolution (MODE). Multiplier updating combined with the ε-constraint technique (IGA-MU) in [6] was stated to be better than conventional GA, but there was no result comparison in this study. Another method, based on the integration of predator-prey optimization, is the Powell search and penalty handling method (PPO-PS-PM) [7], which obtained better results than PPO-PS, PPO-PM, PSO-PS and PSO-PM. The application of a distribution method based on an improved regularity model (IRMDM) was not compared to other methods, not even its own conventional version [8]. An efficient cuckoo algorithm (CA) [9] showed superiority over other methods in [5-8] in terms of better solutions and faster execution time. A modified Real-coded Genetic Algorithm approach using mutation based on random transfer vectors (RCGA-RTVM) was presented in Haghrah, *et al.* [10]. A combination of improved Mühlenbein mutation and RCGA is proposed in Nazari-Heris, *et al.* [11] and the Parallel Multi-objective Genetic Algorithm (PMOGA) is proposed in Feng, *et al.* [12]. A modified dynamic neighborhood learning-based particle swarm optimization (MDNLPSO) [13] and multi-objective quantum-behaved particle swarm optimization (MOQBPSO) [14] obtained better cost than most methods, including conventional PSO. Multi-objective improved artificial physical optimization (MOIAPO) [15] was demonstrated to be more effective than other methods, i.e. MOPSO, MODE, and NSGA-II. Dynamic non-linear programming (DNLP) [16] has shown its potential with much better cost than other methods but emission reduction was not considered as an objective.

The original differential evolution (ODE), developed by Storn and Price in 1997 [17], is a family of effective meta-heuristic algorithms dealing with power system optimization problems considering a non-differentiable objective function, nonlinear constraints and complicated constraints [18]. Apart from that ODE has two main advantages, i.e. fast convergence and few control parameters [19]. However, it still suffers from limitations such as feeble local search ability, low convergence to global optimum solutions, and easily getting trapped in local optima [20]. In Reference [21], Qin, *et al.* report the use of the mutation operation and point out its limits including easy convergence to local optimal solutions and difficulty for the selection of the most appropriate mutation factor. Padhye, *et al.* [22] have suggested elitist selection. Many DE variants have been constructed, such as DE with adaptive mutation [20-21], DE with elitist selection [22], DE with ancestor tree [23], DE with adaptive mutation and elitist selection [24], DE with penalty method [25], and surrogate differential evolution (SDE) [26].

In this study, we propose our NDE method, which uses two new techniques, i.e. modified mutation and modified selection. The two techniques will stop the NDE from suffering the disadvantages of ODE, namely low capability of global convergence, high total number of fitness evaluations and huge number of trial runs for different values of the mutation factor. Furthermore, NDE can cancel the crossover operation and quit crossover selection. In order to test the performance of the proposed NDE, we implemented NDE, ODE and two other versions of DE, i.e. DE with modified mutation (MMDE) and DE with modified selection (MSDE), to solve two different hydrothermal systems. The first one consisted of two thermal units and two hydro units, without considering valve point loading effects on the thermal units, and the second consisted of two hydro units and four thermal units, with considering valve point loading effects. The performance of NDE was evaluated via comparison with ODE, MMDE, MSDE, and other methods.

2 Problem Formulation

The considered hydrothermal system with N_1 thermal units and N_2 hydro units working in M scheduled sub-intervals is mathematically formulated as follows.

2.1 Objective Function

The objective function of the problem aims to determine the task of reducing the thermal units' costs and emissions for the overall scheduled time of M sub-intervals. The fuel cost function neglecting and considering the loading effects are respectively represented in Eqs. (1) and (2) as follows:

$$F_{1i} = \left[a_{si} + b_{si} P_{si} + c_{si} P_{si}^2 \right] \tag{1}$$

$$F_{1i} = \left[a_{si} + b_{si} P_{si} + c_{si} P_{si}^2 + \left| d_{si} \times sin\left(e_{si} \times \left(P_{si}^{min} - P_{si} \right) \right) \right| \right] \tag{2}$$

Emission gas from each thermal unit can be expressed in the form of a quadratic function (See Eq. (3)) and the sum of a quadratic function and an exponential function (See Eq. (4)) [7]:

$$F_{2i} = \alpha_{si} + \beta_{si} P_{si} + \gamma_{si} P_{si}^2 \tag{3}$$

$$F_{2i} = \alpha_{si} + \beta_{si}P_{si} + \gamma_{si}P_{si}^2 + \eta_{si}\,exp(\delta_{si}P_{si}) \tag{4}$$

where α_{si}, β_{si}, γ_{si}, η_{si}, and δ_{si} are the emission coefficients of thermal unit i.

The objective function of the multi-objective problem is converted into a single function by using the sum of the two functions in Eq. (5) [7]:

$$Min\,F = \phi_1\sum_{i=1}^{N_1}F_{1i} + \phi_2\sum_{i=1}^{N_1}F_{2i} \tag{5}$$

where in Eq. (6):

$$\phi_1 + \phi_2 = 1 \text{ and } 0 \le \phi_1, \phi_2 \le 1 \tag{6}$$

2.2 Transmission Grid Constraints and Generator Constraints

2.2.1 Demand-supply Balance Constraint

The relationship of total generated power, load demand and power losses should satisfy the following Eq. (7) rule:

$$\sum_{i=1}^{N_1}P_{si,m} + \sum_{j=1}^{N_2}P_{hj,m} - P_{L,m} - P_{D,m} = 0;\, m = 1,\ldots, M \tag{7}$$

where m is the subinterval index; power loss $P_{L,m}$ is calculated by using Kron's loss formula [2].

2.2.2 Limits on Power Output

The operation ranges of hydro generation and thermal generation are bounded by their capability in Eq. (8) as follows:

$$P_{si,min} \le P_{si,m} \le P_{si,max} \text{ and } P_{hj,min} \le P_{hj,m} \le P_{hj,max} \tag{8}$$

2.3 Hydraulic Constraints

2.3.1 Used Water-available Water Balance Constraint

The total water discharged via the hydro turbines over the entire scheduled time horizon should be the same as the available water, as shown in Eq. (9):

$$\sum_{m=1}^{M}t_m q_{j,m} = W_j\,;\, j = 1,\ldots, N_2 \tag{9}$$

where $q_{j,m}$ is the water discharge of hydro plant j in interval m obtained by the following Eq. (10):

$$q_{j,m} = a_{hj} + b_{hj} P_{hj,m} + c_{hj} P_{hj,m}^2 \tag{10}$$

2.3.2 Limits on Water Discharge

The following limitations should be imposed on water discharge as in Eq. (11):

$$q_{j,min} \leq q_{j,m} \leq q_{j,max}; \quad j = 1, 2, ..., N_2; m = 1, 2, ..., M \tag{11}$$

where $q_{j,max}$ and $q_{j,min}$ are the highest and lowest discharges from hydro plant j.

3 Proposed Novel Differential Evolution

3.1 Original Differential Evolution

Each individual U_x (x = 1, …, N_{pop}) in population (N_{pop} solutions) is initialized within its boundaries as in the following expressionin Eq.(12):

$$U_x = U_{min} + rand * (U_{max} - U_{min}); \; x = 1, ..., N_{pop} \tag{12}$$

The mutation of ODE uses three randomly different existing solutions in Eq. (13) as follows:

$$V_x = U_1 + MF(U_2 - U_3); x = 1, ..., N_{pop} \tag{13}$$

Crossover is then performed by the definition below in Eq. (14):

$$W_x = \begin{cases} V_x & if \quad RN_x \leq CF \\ U_x & otherwise \end{cases} ; x = 1, ..., N_{pop} \tag{14}$$

where RN_x is a random number between 0 and 1 for individual x and is the crossover factor, which is chosen in the range between 0 and 1.

At the end of each iteration, selection is carried out by using the following Eq.(15):

$$U_x = \begin{cases} W_x & if \quad Fitness(W_x) \leq Fitness(U_x) \\ U_x & otherwise \end{cases} \tag{15}$$

3.2 The Proposed Novel Differential Evolution

The proposed NDE method is an improved version of ODE obtained by proposing two modifications of the mutation and selection techniques. The two modified techniques are explained in detail below.

3.2.1 Modified Mutation Technique

As seen from Eq. (13), ODE uses an updated step size based on two random solutions for producing new solutions by mutation. The updated step size is always used in the search process, resulting in the possibility of a local optimum as a result of premature convergence or a nearby global optimum. Thus, the following modified mutation technique is suggested:

rand/1: $V_x = U_1 + MF(U_2 - U_3)$ (16)

rand/2: $V_x = U_1 + MF(U_2 - U_3 + U_4 - U_5)$ (17)

best/1: $V_x = S_{best} + MF(U_1 - U_2)$ (18)

best 2: $V_x = S_{best} + MF(U_1 - U_2 + U_3 - U_4)$ (19)

current-to-best: $V_x = U_x + MF(S_{best} - U_x + U_1 - U_2)$ (20)

Among the formulas (Eqs. (16) to (20), global search ability is enhanced by using rand/1 and rand/2, while local search ability is concentrated by the application of best/1 and best/2. It can be seen that the rand modes aim to search solutions nearby the existing solutions and the zone of search is extensive but the two best modes search the zone around the so-far best solution and the zone of search is small. All in all, the rand modes and the best modes must satisfy different limitations on fast convergence with a global optimum if they are applied separately. The rand modes are promising for global search but they are weak for local search, while the two best modes are not highly effective for global search but they are capable of improving local search. In addition, current-to-best mode also has the same impact on the result as the mode of rand/2. Therefore, the selection of either current-to-best or rand/2 is a stochastic determination. For this operation, a uniform random number ε_1 is produced in the range between 0 and 1; this number is compared to probability at 0.5. If ε_1 is higher than 0.5, the rand/2 mode is employed, otherwise current-to-best is chosen. In our paper, we propose modified mutation based on the five suggested mutation modes including rand/1, rand/2, best/1, best/2, and current-to-best, where rand/1, rand/2 and current-to-best belong to the global search group while best/1 and best/2 belong to the local search group. The decision to employ the global search group or the local search group is based on a comparison between a predetermined tolerance τ and fitness ratio θ_x, which is calculated by the following expression in Eq.(21):

$$\theta_x = \left(Fit_x - Fit_{best}\right) / Fit_{best} \quad (21)$$

Because fitness ratio θ_x is higher than predetermined tolerance τ, solution x is far away from the so-far best solution and it is likely that the global search group is a better choice than the local search group. Thus, the rand modes are used in this case. However, when θ_x is equal to or lower than τ, solution x is close to the so-far best solution and the local search group is a more appropriate choice. Therefore, best modes are started in this case. On the other hand, the condition for the selection of either rand/1 or rand/2, and best 1/2 or best/2 is also constructed. Thus, mutation mode parameter (MMP) is proposed and compared to a random number.

3.2.2 Modified Selection Technique

The modified selection technique has better performance than conventional selection in ODE in terms of optimal solution quality and solution quality stabilization. In the modified technique, $U = [U_1, U_2, ..., U_x...,..., U_{Npop}]$ and $W = [W_1, W_2, ...,W_{x},..., W_{Npop}]$ are grouped into one and then N_{pop} solutions with better fitness function are kept.

4 Implementation of the Proposed NDE for the Considered EEHTSD Problem

4.1 Initialization and Handling Equality Constraints

In the EEHTSD problem, each solution U_x represents thermal units $P_{si,m,x}$ and water discharge $q_{j,m,x}$ and is initialized in Eqs. (22) and (23) as below:

$$P_{si,m,x} = P_{si,min} + rand * (P_{si,max} - P_{si,min});\ i = 2,...,N_1;\ m = 1,..., M \tag{22}$$

$$q_{j,m,x} = q_{j,min} + rand * (q_{j,max} - q_{j,min});\ j = 1,...,N_2;\ m = 1,..., M-1 \tag{23}$$

Water discharge $q_{j,m,x}$ is first obtained by using Eq.(9) and then hydro generation is determined by using Eq.(10) [9]. Finally, $P_{s1,m,x}$ is obtained by using Eq.(7) [9].

4.2 Fitness Function Evaluation

The quality of all solutions can be evaluated via the following fitness function in Eq. (24):

$$Fitness_x = \sum_{m=1}^{M}\sum_{i=1}^{N_1} F_i(P_{si,m,x}) + K_s \sum_{m=1}^{M}(PT_{1,m,x})^2 + K_q \sum_{j=1}^{N_2}(PT_{2,j,x})^2 \tag{24}$$

where $PT_{1,m,x}$ is the amount of penalty for slack thermal units in each subinterval according to solution x; $PT_{2,j,x}$ is the amount of penalty for slack discharged water of hydro unit j according to solution x [9]; and K_s and K_q are penalty factors.

4.3 Generating New Solutions and Fixing Boundary Violations

The proposed NDE can produce new solutions by using the modified mutation technique. Then all new solutions are checked and fixed for limitations so they are always within their feasible zone, as follows:

$$U_x = \begin{cases} U_{max} & if \;\; U_x > U_{max} \\ U_{min} & if \;\; U_x < U_{min} \\ U_x & otherwise \end{cases} \tag{25}$$

4.4 Entire Computing Process

The details of the overall procedure of the proposed NDE for solving the two HTS problems are as follows:

Step 1: Select NDE parameters, i.e. number of individuals N_{pop}, maximum iteration number G_{max}, mutation mode parameter *MMP*, mutation factor *MF*, and predetermined tolerance τ.
Step 2: Initialize the population randomly using Eqs. (22) and (23).
Step 3: Calculate hydro generation and slack thermal generation.
Step 4: Calculate the fitness value for all new solutions using Eq. (24) and choose the so-far best solution S_{best} that has the lowest fitness value; set the initial iteration counter $G = 1$.
Step 5: Perform modified mutation to generate new solutions; verify limitations and fix using Eq. (25).
Step 6: Calculate hydro generation and slack thermal generation.
Step 7: Calculate the fitness function for the new solutions using Eq. (24).
Step 8: Carry out modified selection to keep N_{pop} best solutions.
Step 9: Find the best solution S_{best} with the lowest fitness value.
Step 10: If $G < G_{max}$, $G = G + 1$ and return to Step 5. Otherwise stop.

5 Numerical Results

The performance of the NDE method was tested on two hydrothermal systems. The first system had two hydropower plants and two thermal plants scheduled in 3 subintervals with 8 hours for each and the second system had two hydropower plants and four thermal plants scheduled in 4 subintervals with 12 hours for each. The data of the first system and the second system were taken from [5] and [7] respectively. In addition, ODE and its two improved versions, MMDE and MSDE, were also implemented to illustrate the impact of each modification on ODE and the effectiveness of application of the two modifications on ODE. The four methods were implemented under the same conditions on the same Matlab platform and the same PC with a 2 GHz processor and 2 GB of RAM, and with 50 independent trials for each case study.

5.1 Analysis of Control Parameter Impact on the Proposed Method

The impact of the control parameters on the results obtained by the proposed method was analyzed by setting them to different values. For the sensitivity test, the economic load dispatch of test System 1 was carried out according to the following five scenarios.

In the first and the second scenario, we tested the impact of N_{pop} and G_{max} on the obtained results by setting them to 7 values with a change of 10 while MMP = 0.6, $MF = 0.6$ *and* $\tau = 10^{-2}$ were fixed. In addition, $G_{max} = 50$ was adopted for the first scenario and $N_{pop} = 30$ was adopted for the second scenario. In the third and the fourth scenario, the impacts of *MMP* and *MF* were observed by setting them to 5 values from 0.2 to 1 with an interval of 0.2 and setting N_{pop}, G_{max} and τ to 30, 50 and 10^{-2}, respectively. Meanwhile, running different values of *MMP*, *MF* was fixed at 0.6 and running different values of *MF*, *MMP* was also fixed at 0.6. For the last scenario, testing the sensitivity of τ on the results, we set τ to five values, i.e. 10^{-1}, 10^{-2}, 10^{-3}, 10^{-4}, and 10^{-5}, while fixing $N_{pop} = 30$, $G_{max} = 50$, MMP = 0.6, and $MF = 0.6$. The results of these five scenarios in terms of minimum cost, average cost, maximum cost, standard deviation cost and computational time are reported in Tables 1 to 5. As can be seen from Tables 1 and 2, the cost reduction could be improved when N_{pop} and G_{max} were increased, reaching a best value of \$64606.0037 at $N_{pop} = 30$ and $G_{max} = 50$. When N_{pop} and G_{max} were respectively less than 30 and 50, this best cost was not obtained. Better cost than \$64606.0037 was not obtained when N_{pop} and G_{max} were increased to higher values, i.e. 40, 50, 60 and 70 for N_{pop} and 60, 70, 80, 90 and 100 for G_{max}. In fact, the best cost could not be improved, whereas other costs such as average cost, maximum cost and standard deviation cost could be much improved. For instance, these costs were \$64606.6699, \$64623.2675 and \$2.7150 at $N_{pop} = 30$ and $G_{max} = 50$, and \$64606.008, \$64606.019 and \$0.0031 at $N_{pop} = 70$ and G_{max} = 50. Similarly, these costs were \$64606.224, \$64609.298 and \$0.6633 at N_{pop} = 30 and $G_{max} = 100$. On the other hand, computation time tended to be higher when N_{pop} and G_{max} were set to higher values. Clearly, population size and maximum iteration number had the same impact on the results, namely better results with higher values.

The results in Table 3 indicate that *MMP* is effective when it is set to 0.2, 0.4 or 0.6 for obtaining the lowest costs, while the values of 0.8 and 1 did not result in the best cost. However, standard deviation cost was more stable when *MMP* was set to higher values. Table 4 shows that $MF = 0.6$ was the best value, leading to the best cost of \$64606.0037 and acceptable standard deviation cost, while other values of *MF*, i.e. 0.2, 0.4, 0.8 and 1, could not enable the proposed method to reach to this optimum. The lowest costs shown in Table 5 tell us that $\tau = 10^{-1}$, 10^{-2} can result in a best cost of \$64606.0037, while the three remaining values did not enable the proposed method to find this optimal solution. In addition, different values of τ had less impact on the search ability stabilization once standard deviations were from 1.7 to 5.2.

Table 1 Results from the proposed method with different values of Npop.

N_{pop}	Lowest cost (\$)	Mean cost (\$)	Highest cost (\$)	Std. dev (\$)	CPU (s)
10	64646.74	65263.155	68809.133	806.4563	0.24
20	64606.058	64647.282	65202.939	92.9966	0.39
30	64606.0037	64606.6699	64623.2675	2.7150	0.45
40	64606.0037	64606.015	64606.082	0.0165	0.75
50	64606.0037	64606.01	64606.044	0.0086	1.02
60	64606.0037	64606.009	64606.028	0.0048	1.24
70	64606.0037	64606.008	64606.019	0.0031	1.51

Table 2 Results from the proposed method with different values of Gmax.

G_{max}	Lowest cost (\$)	Mean cost (\$)	Highest cost (\$)	Std. dev (\$)	CPU (s)
40	64606.0200	64607.147	64623.473	2.7178	0.39
50	64606.0037	64606.6699	64623.2675	2.715	0.45
60	64606.0037	64606.62	64620.92	2.4614	0.76
70	64606.0037	64606.423	64618.135	1.7571	0.85
80	64606.0037	64606.238	64613.065	1.0328	1.01
90	64606.0037	64606.892	64622.488	2.9258	1.12
100	64606.0037	64606.224	64609.298	0.6633	1.24

Table 3 Results from the proposed method with different values of MMP.

MMP	Lowest cost (\$)	Mean cost (\$)	Highest cost (\$)	Std. dev (\$)	CPU (s)
0.2	64606.0037	64616.9598	64702.3325	22.2704	0.48
0.4	64606.0037	64613.2323	64776.5128	26.1207	0.51
0.6	64606.0037	64606.6699	64623.2675	2.715	0.45
0.8	64606.0068	64606.1664	64608.7177	0.3859	0.50
1	64606.1245	64607.6459	64614.3376	1.5241	0.51

Table 4 Results from the proposed method with different values of MF.

MF	Lowest cost (\$)	Mean cost (\$)	Highest cost (\$)	Std. dev (\$)	CPU (s)
0.2	64645.761	64956.814	66394.439	284.3881	0.44
0.4	64607.878	64666.446	64924.468	65.9035	0.48
0.6	64606.0037	64606.6699	64623.2675	2.715	0.45
0.8	64606.831	64617.665	64658.512	9.1331	0.42
1	64670.351	64830.28	65428.914	128.116	0.47

Table 5 Results from the proposed method with different values of τ.

τ	10^{-1}	10^{-2}	10^{-3}	10^{-4}	10^{-5}
Lowest cost ($)	64606.0037	64606.0037	64606.0415	64607.1557	64607.4206
Mean cost ($)	64607.4431	64606.6699	64607.0266	64614.2236	64613.1142
Highest cost ($)	64631.7052	64623.2675	64616.9378	64630.2314	64627.1580
Std. dev. ($)	4.4141	2.7150	1.7016	5.1882	4.2362
CPU (s)	0.5	0.45	0.49	0.52	0.52

In summary, the obtained results from the proposed method, i.e. minimum cost and standard deviation, were very sensitive to the values of N_{pop} and G_{max}, and slightly sensitive to the values of *MMP*, *MF* and τ. Besides that, computation time was also much influenced by small values and high values of N_{pop} and G_{max}, while *MMP*, *MF* and τ had no impact on computation time. For the other test cases in this paper, we selected the values of N_{pop} and G_{max} by experiment while *MMP*, *MF* and τ were respectively set to 0.6, 0.6 and 10^{-2}. A comparison of results from the proposed method with those from the other methods are presented in the following section.

5.2 Test System 1

This section focuses on the implementation of the four methods for solving the first system, after which the numerical results are summarized and analyzed. The four methods were run for fuel cost dispatch, emission dispatch and fuel cost-emission dispatch by setting population size and maximum iteration number to 30 and 50, respectively. As a result, Table 6 and Table 7 report the minimum value, mean value, highest value and standard deviation value of the fitness function for 50 trial runs and the mean computation time for each run. The lowest-cost comparison indicates that the value obtained by the proposed NDE was respectively lower than ODE, MMDE and MSDE by $0.8035, $0.1666 and $0.1257. Similarly, the proposed NDE obtained lower cost than these methods by $32.6297, $13.0369, and $14.9227 for mean cost, and by $106.8649, $25.2055, $27.6303 for highest cost, and by $19.8135, $7.203, $6.5076 for standard deviation cost. Clearly, for the fuel cost dispatch, the two modifications of the proposed NDE managed to find an improvement on the solution quality as reflected in the lowest cost, quality stabilization as reflected in the mean, the highest and the standard deviation. Besides that, each modification carried out on ODE was also efficient, since both MMDE and MSDE had better minimum cost and standard deviation cost than ODE. The same figures were also seen for the emission dispatch based on comparisons of the minimum, average, maximum and standard deviation values were done.

The curves reflecting fitness vs. iteration for the fuel cost dispatch and emission dispatch are depicted in Figures 1 and 2. The curves show the advantage of the proposed NDE over the three other DE methods. For the case of multi-objective optimization, the best compromise solution must be determined among a set of non-dominant solutions that have been obtained by using different values for these two weight factors. In fact, when the selection of the fuel cost weight is close to 1, the obtained solution produces very low costs but very high emissions and when setting the fuel cost weight close to 0 and the emission weight close to 1, the obtained solution produces very high costs but very low emissions. There is clearly a trade-off between fuel cost and emission for this solution. Consequently, there must exist a set of solutions. Determination of one solution for multi-objective optimization can be done by using a fuzzy method [27]. For the case of determination of a compromise solution for multi-objective optimization, a set of 26 non-dominant solutions is found and then the priority factor μ_D^k is obtained as described in [27].

The non-dominant solutions and the best compromise solution of the proposed NDE are shown in Figure 3. Similarly, the best compromise solutions have also been obtained for ODE, MMDE and MSDE. As a result, NDE, MMDE and MSDE obtained the same best cost and best emission with $65,054.9 and 593.9688 lb, which were both lower than those from ODE, $65,055.4 and 594.2 lb. Based on the indication from the three dispatch cases, it can be concluded that the two modifications of the ODE method proposed in this paper are very effective and robust.

Table 6 Result comparisons for fuel cost dispatch of system 1.

Method	ODE	MMDE	MSDE	NDE
N_{pop}	30	30	30	30
G_{max}	50	50	50	50
Lowest cost ($)	64606.8072	64606.1703	64606.1294	64606.0037
Mean cost ($)	64639.2996	64619.7068	64621.5926	64606.6699
Highest cost ($)	64730.1324	64648.4730	64650.8978	64623.2675
Std. dev. ($)	22.5285	9.9180	9.2226	2.7150
CPU (s)	0.46	0.52	0.51	0.45

Table 7 Result Comparisons for Emission Dispatch of System 1.

Method	ODE	MMDE	MSDE	NDE
N_p	30	30	30	30
G_{max}	50	50	50	50
Best cost ($)	566.7811	564.9761	565.2230	564.7405
Mean cost ($)	584.0673	584.9637	579.0704	566.8626
Worst cost ($)	610.9993	608.1058	600.1438	588.3300
Std. dev. ($)	9.7505	7.7831	8.5398	3.8024
CPU (s)	0.47	0.52	0.52	0.47

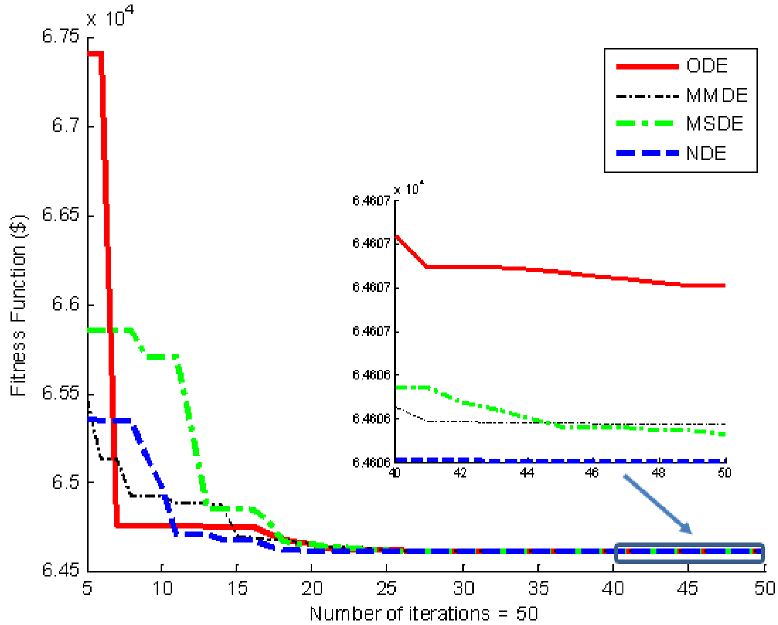

Figure 1 Convergence curves obtained by four DE variants for economic dispatch.

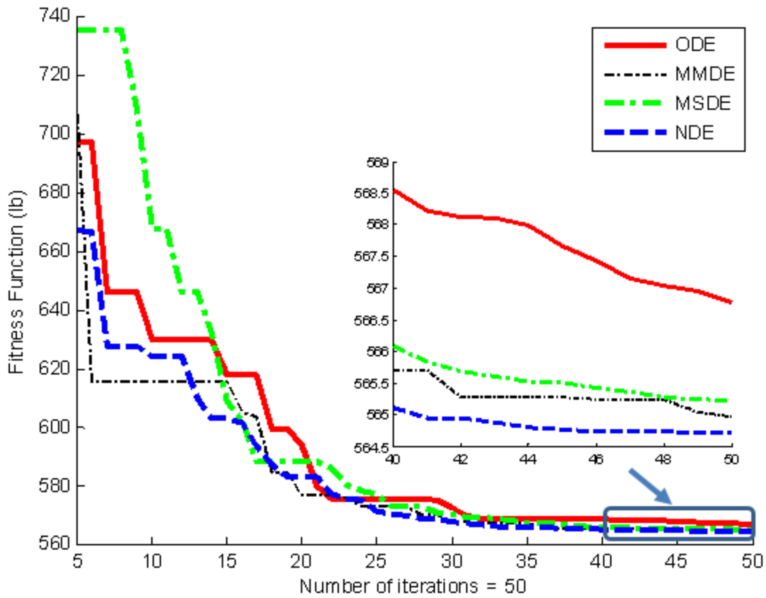

Figure 2 Convergence curves obtained by four DE variants for emission dispatch.

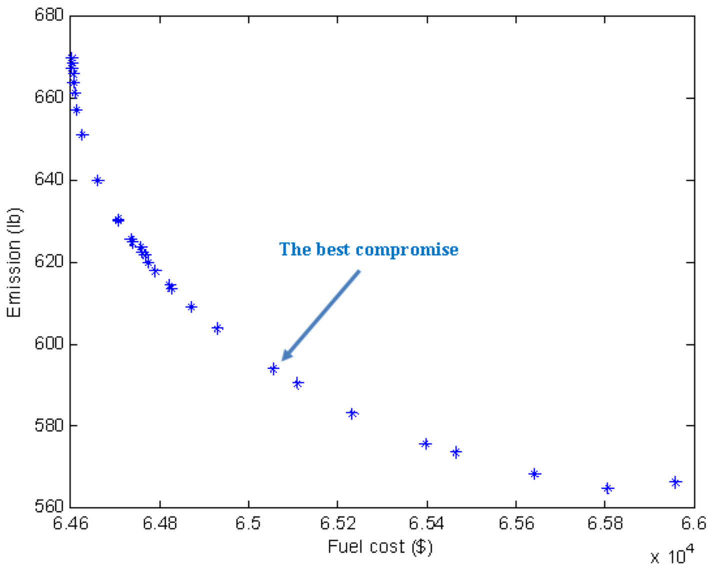

Figure 3 Set of non-dominant solutions and best compromise obtained by the proposed NDE.

In order to clarify the performance of the proposed NDE, the results obtained by NDE and other methods, from [5,7,9], are shown in Table 8 for the system. The comparisons for three dispatch cases indicate that the proposed NDE obtained the lowest cost for economic dispatch, excluding the comparison with CA [9] (which had the same cost) and the lowest emission for emission dispatch and the lowest cost and emission for the environmental economic dispatch.

Table 8 Result comparison for system 1.

Method	Fuel dispatch		Emission dispatch		Compromise dispatch		
	Cost ($)	**CPU (s)**	**Emission (lb)**	**CPU (s)**	**Cost ($)**	**Emission (lb)**	**CPU (s)**
RCGA[5]	66,031	21.63	586.14	20.27	-	-	-
NSGA-II [5]	-	-	-	-	66,331	618.08	27.85
MODE [5]	-	-	-	-	66,354	619.42	30.71
SPEA-2 [5]	-	-	-	-	66,332	618.45	34.87
PSO-PM [7]	65,741	18.25	585.67	18.00	65,821	620.78	18.98
PSO [7]	65,241	18.32	579.56	18.31	65,731	618.78	19.31
PPO-PM [7]	64,873	16.14	572.71	15.93	65,426	612.34	16.53
PPO [7]	64,718	15.99	569.73	15.18	65,104	601.16	16.34
PPO-PS-PM [7]	64,689	15.98	568.78	15.92	65,089	600.24	16.15
PPO-PS [7]	64,614	15.89	564.92	15.45	65,058	594.18	16.74
CA [9]	64,606	0.7	564.81	0.65	65,055	593.97	0.76
NDE	64,606	0.45	564.71	0.47	65,054.9	593.9688	0.46

Furthermore, the execution time from the proposed NDE was also the shortest. Clearly, there is enough evidence of better solution quality reflected by lower costs and lower emissions and faster convergence reflected by shorter execution time to conclude that the proposed NDE is more efficient than the other methods. The optimal solutions obtained by the proposed method for System 1 are given in the Appendix.

5.3 Test System 2

In order to implement the proposed NDE for System 2, the number of individuals and the maximum number of iterations were set to 50 and 700, respectively. The cost and emission results for the fuel cost dispatch, emission dispatch and environmental dispatch are compared in Table 9. Lower costs and emissions were obtained by the proposed NDE compared to the best method from each study, which indicates the superiority of NDE over these methods. Among the methods applied in [5], NSGA-II was the best one. Equally, IGA-MU was the best method in [6] and PPO-PS was the best method in [7]. Compared to the best methods for the fuel cost dispatch, the proposed method obtained lower fuel costs than SA-BGA [3] by $5,921, IGA-MU [6] by $1,742, PPO-PS [7] by $770, CA [9] by $192.

Table 9 Result comparison for the second system.

Method	Economic dispatch		Emission dispatch		Economic emission dispatch		
	Cost ($)	CPU (s)	Emission (lb)	CPU (s)	Cost ($)	Emission (lb)	CPU (s)
SA-BGA [3]	70,718	-	23,200	-	73,612	26080	1492
RCGA [5]	66,516	40.36	23,222	41.98	-	-	-
NSGA-II [5]	-	-	-	-	68,333	25,278	45.42
MODE [5]	-	-	-	-	68,388	25,792	46.76
SPEA-2 [5]	-	-	-	-	68,392	26,005	57.02
GA-MU [6]	67,751	90.15	23,223	78.27	68,521	26,080	96.10
IGA-MU [6]	66,539	51.63	23,223	42.87	68,492	26,080	53.54
PSO-PM [7]	66,349	33.14	23,167	33.63	67,994	25,902	34.11
PSO [7]	66,223	32.15	23,112	32.34	67,892	25,773	34.52
PPO-PM [7]	65,912	21.03	23,078	21.18	67,211	25,606	22.04
PPO [7]	65,885	21.45	22,966	21.56	67,170	25,601	22.11
PPO-PS-PM [7]	65,723	21.12	22,912	24.74	67,092	25,600	24.90
PPO-PS [7]	65,567	22.00	22,828	21.98	66,951	25,596	22.76
IRMDM [8]	68,000	-	23,031.57	-	-	-	-
CA [9]	64,989	16.4	22,818	16.8	66,530	25,247	16.30
NDE	64,797	11.2	22,817.9	10.9	66,511	25,138	11.1

The superiority of the proposed NDE over the other methods can also be seen from the environmental dispatch, where the proposed NDE obtained lower emissions than SA-BGA [3], IGA-MU [6], PPO-PS [7], and IRMDM [8] by

382 lb, 405 lb, 10 lb, and 214 lb, respectively. Equally, the best cost and best emission for the environmental economic dispatch obtained by NDE were also better than PPO-PS [7] by \$440 and 458 lb, CA [9] by \$19 and 109lb, respectively. The result comparisons show that the proposed NDE obtained better solutions than all other methods for the three cases. The execution time comparison shows that the proposed NDE is the fastest method, with an execution time of around 11 seconds, while the other methods needed from 22 seconds to 1492 seconds. Consequently, it can be concluded that the proposed NDE was very effective for System 2 with nonconvex fuel cost function. The optimal solutions obtained by the proposed method for the system are given in the Appendix.

6 Conclusion

This paper presented the application of the NDE method for solving two hydrothermal systems related to the environmental economic hydrothermal system dispatch problem. The proposed NDE uses two modifications of DE, i.e. modified mutation and modified selection. The two modifications enable the proposed NDE to obtain higher solution quality with faster convergence than the original DE method. As compared to other methods, the proposed NDE is also more effective in terms of solution quality and speed. Consequently, it can be concluded that the proposed NDE is a very promising method for solving the EEHTSD problem.

Nomenclature

a_{hj}, b_{hj}, c_{hj}	=	Water discharge coefficients of hydro plant j
$a_{si}, b_{si}, c_{si}, d_{si}, e_{si}$	=	Coefficients of the i^{th} thermal plant fuel cost
CF	=	Crossover factor
F_{1i}, F_{2i}	=	Fuel cost and emission of thermal unit i
Fit_{best}, Fit_x	=	Fitness function of the best solution and solution x
$P_{D,m}, P_{L,m}$	=	Load demand and power loss in subinterval m
$P_{hj,max}, P_{hj,min}$	=	Maximum and minimum generation of hydro plant j
$P_{si,max}, P_{si,min}$	=	Maximum and minimum generation of thermal plant i
S_{best}	=	The best solution among the population
t_m	=	Number of hours for subinterval m
U_1, U_2, U_3, U_4, U_5	=	Random solutions
U_{max}, U_{min}	=	Maximum and minimum values of each solution U_x
W_j	=	Volume of available water for hydro unit j
Φ_1, Φ_2	=	Weight factors related to fuel cost and emission

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Appendix

Table A1 Optimal solutions obtained by NDE for economic dispatch of system 1.

Sub-interval	P_{s1} (MW)	P_{s2} (MW)	P_{h1} (MW)	P_{h2} (MW)
1	168.6443	415.9232	245.3859	98.5777
2	219.1000	570.2528	305.5364	157.0040
3	202.1990	518.5214	285.1229	137.4259

Table A2 Optimal solutions obtained by NDE for emission dispatch of system 1.

Sub-interval	P_{s1} (MW)	P_{s2} (MW)	P_{h1} (MW)	P_{h2} (MW)
1	299.9430	361.8473	214.2187	56.0222
2	299.9646	439.8818	328.0810	186.2548
3	299.9070	407.4686	291.2719	147.0790

Table A3 Optimal solutions obtained by NDE for compromise case of system 1.

Sub-interval	P_{s1} (MW)	P_{s2} (MW)	P_{h1} (MW)	P_{h2} (MW)
1	230.5454	371.6319	237.1409	90.1952
2	289.7196	487.9712	312.0445	163.5092
3	270.1858	449.1689	286.3401	138.7865

Table A4 Optimal solutions obtained by NDE for economic dispatch of system 2.

Sub-interval	Duration (h)	P_{s1} (MW)	P_{s2} (MW)	P_{s3} (MW)	P_{s4} (MW)	P_{h1} (MW)	P_{h2} (MW)
1	12	98.5093	30.0019	124.9080	139.7569	198.8837	323.5380
2	12	98.5398	30.0038	124.9091	229.5633	223.6900	416.8517
3	12	98.5389	30.7413	40.9174	229.6754	231.2379	388.9879
4	12	98.5398	112.6763	209.8098	229.5196	224.7685	457.3343

Table A5 Optimal solutions obtained by NDE for emission dispatch of system 2.

Sub-interval	Duration (h)	P_{s1} (MW)	P_{s2} (MW)	P_{s3} (MW)	P_{s4} (MW)	P_{h1} (MW)	P_{h2} (MW)
1	12	72.2177	133.6229	136.0800	91.6348	169.9480	312.2984
2	12	78.8182	142.2484	147.7182	99.8561	247.4368	407.8851
3	12	75.6884	137.8535	141.6653	95.4361	208.3657	360.6454
4	12	102.0916	167.7859	184.5514	129.3665	249.9996	500.0000

Table A6 Optimal solutions obtained by NDE for compromise case of system 2.

Sub-interval	Duration (h)	P_{s1} (MW)	P_{s2} (MW)	P_{s3} (MW)	P_{s4} (MW)	P_{h1} (MW)	P_{h2} (MW)
1	12	20.1145	112.6993	125.4129	139.6429	187.6690	330.0879
2	12	96.9933	112.6802	125.4402	139.7598	223.6429	425.4145
3	12	98.4666	112.6725	124.9079	139.5154	216.3503	327.4174
4	12	98.5230	138.6176	209.4597	139.6444	249.8765	497.3240