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Emission-constrained Dynamic Economic Dispatch using Opposition-based Self-adaptive Differential Evolution Algorithm

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Abstract *–* *This paper presents an opposition-based self-adaptive differential evolution algorithm for emission-constrained dynamic economic dispatch (ECDED) problem with non-smooth fuel cost and emission level functions. ECDED is an optimization problem with an objective to determine optimal combination of power outputs for all committed generating units over a certain period of time in order to minimize the total fuel cost and emission while satisfying dynamic operational constraints and load demand in each interval. A multi-objective function is formulated by assigning the relative weight to each of the objective and then optimized by opposition-based self-adaptive differential evolution algorithm. The convergence rate of differential evolution is improved by employing opposition-based learning scheme and a self-adaptive procedure for control parameter settings. The validity and effectiveness of the proposed approach is demonstrated by a test system with five thermal generating units. The simulation results show that the proposed approach provides a higher quality solution with better performance.*

Keywords **–** Differential evolution, emission-constrained dynamic economic dispatch, multi-objective optimization, ramp-rate limits, valve-point effects.

1. INTRODUCTION

Thermal power plants while generating power, simultaneously release toxic gases such as SO_2 and NO_2 from boiler by burning the coal as fuel. In addition, particulate matter pollutes the whole atmosphere when it exceeds the limit. Due to the increased awareness for the environmental protection and the introduction of the Clean Air Act Amendments, utilities have been forced with modifications in the design and operation of the thermal power plants for controlling emissions such as SO_2, CO_2 and NOx [1]. Hence, it has become necessary to supply power with minimum emission as well as with minimum total fuel cost.

Various strategies like installing post combustion cleaning system, switching to low sulphur content coal and emission dispatching have been proposed for minimizing emission. Emission dispatching is an attractive short-term alternative in which both emission and fuel cost are minimized. Proper allocation of generation reduces the fuel leading to emission control. It is easy to implement and requires only a minor modification of the basic economic dispatch to include emission. The cost minimum condition corresponds to minimum cost with considerable amount of emission. Similarly, the emission minimum condition produces minimum emission with higher deviation from the minimal cost. A co-ordination between cost and emission becomes necessary and the system as a whole is considered for cost minimum and controlled emission.

Including the emissions either in the objective function or treating emissions as additional constraints has been considered in a number of publications. El-Keib *et al*. [2] have presented a general formulation of the environmental constrained economic dispatch problem. This solution algorithm is based on the Lagrange relaxation method, by adding separate small module to the existing economic dispatch. El-Keib *et al*. [3] presented the solution to the emission-constrained economic dispatch problem, which is linear programming based and uses gradient projection method to guarantee feasibility of the solution. Recently neural network [4], [5], genetic algorithms [6], [7], fuzzy logic [8], evolutionary programming [9] and multi-objective evolutionary algorithms [10] have been applied to solve the combined economic emission dispatch problem. Simulated annealing technique based on an interactive fuzzy satisfying method for economic emission load dispatch problem is discussed in [11].

In the traditional combined economic and emission dispatch problem, it is assumed that the amount of power to be supplied by a given set of units is constant for a given interval of time, and attempts to minimize the emission and cost of supplying this energy are subject to constraints on static behavior of the generating units. Inclusions of ramp-rate constraints distinguish the ECDED problem from traditional, static emission controlled economic dispatch problem. ECDED is a heavily constrained optimization problem due to non-convex fuel cost and emission functions, and ramp-rate constraints of the generators. ECDED is a method to schedule the committed generating outputs with the predicted load demand over a certain period to operate a power system most economically with reduced emission condition. It is an accurate formulation of economic dispatch problem, but also the most difficult dynamic optimization problem. Basu [12] developed Particle Swarm Optimization (PSO) based goal-attainment method for solving dynamic economic

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emission dispatch. The PSO method may prove to be very effective in solving nonlinear economic dispatch problem, but PSO method often provides a fast and acceptable (local optimum) solution, for the heavily constrained optimization problems like ECDED problem.

Differential evolution (DE) is a simple yet powerful evolutionary algorithm for global optimization introduced by [13]. Like other evolutionary algorithms, DE is a population-based, stochastic global optimizer capable of working reliably in nonlinear environments. DE is a robust statistical method for cost minimization, which does not make use of single nominal parameter vector but instead uses a population of equally important vectors. The fittest of an offspring competes one to one with of the corresponding parent, which is different from the other evolutionary algorithms. In this article, opposition-based self-adaptive differential algorithm has been developed for ECDED problem. The proposed algorithm is applied to ECDED problem of five-unit sample test system for the sake of comparison with the recently reported paper [12]. Choosing control parameters, that is, scaling factor and crossover rate, in a DE algorithm is a problem dependent task which requires previous experience of the user. In the proposed algorithm, the control parameters such as scaling factor and crossover rate are not required to be pre-defined. A self-adaptive mechanism is used to change these control parameters during the evolutionary process. The better values of these control parameters lead to better individuals, which, in turn, are more likely to survive. The convergence characteristic of the DE algorithm is enhanced by incorporating opposition-based learning for population initialization and for generation jumping. The comparison of simulation shows that the opposition-based self-adaptive differential evolution algorithm out performs the PSO method in terms of solution accuracy.

2. FORMULATION OF ECDED PROBLEM

The ECDED is formulated as a multi-objective optimization problem, which should minimize both the fuel cost and emission subject to satisfy the operational constraints of the generators and meet the load demand plus transmission loss in each interval of the scheduling horizon.

A bi-objective function of ECDED problem can be expressed as the combination of economic and emission objectives in the following form:

$$F = W_1 * \sum_{t=1}^{T}\sum_{i=1}^{N} F_{it}(P_{it}) + W_2 * \sum_{t=1}^{T}\sum_{i=1}^{N} E_{it}(P_{it}) \quad (\$) \quad (1)$$

where F is the total operating cost over the whole dispatch period, T is the number of hours in the time horizon, N is the total number of dispatchable units, $W_1$is the weighting factor for economic objective such that its value should be within the range 0 and 1, and W_2 is the weight factor for emission objective which is given by $W_2 = (1- W_1)$, and $F_{it}(P_{it})$ and $E_{it}(P_{it})$ are fuel cost and emission in terms of real power output P_{it} at time t, respectively. The fuel cost function of the i^{th} unit including valve-point effects [14], [15] can be expressed as

$$F_{it}(P_{it}) = a_i P_{it}^2 + b_i P_{it} + c + \left| e_i \sin(f_i \, (P_{i\min} - P_{it})) \right| \; (\$/h) \quad (2)$$

where a_i, b_i, and c_i are cost coefficients of i^{th} generating unit, e_i, f_i are constants from the valve-point effect of the i^{th} generating unit, P_i is the power output of the i^{th} unit in megawatts at time t. In this article, a nitrogen oxide NOx that is more harmful is taken as the selected index from the viewpoint of environment conservation. The NOx emission of the thermal power station having n generating units at interval t in the scheduling horizon is represented by the sum of quadratic and exponential functions of power generation of each unit. The emission due to i^{th} thermal generating unit can be expressed as

$$E_{it}(P_{it}) = \alpha_i P_{it}^2 + \beta_i P_{it} + \gamma_i + \eta_i \exp(\delta_i P_{it}) \text{ (lb)} \quad (3)$$

where α_i, β_i, γ_i, δ_i and, η_i, are emission curve coefficients of i^{th} generating unit .

The minimization of the fuel cost and emission are subjected to the following equality and inequality constraints:

1. *Real power balance constraint:*

$$\sum_{i=1}^{N} P_{it} - P_{Dt} - P_{Lt} = 0 \quad (4)$$

where t = 1, 2,…,T. P_{Dt} is the total power demand at time t and P_{Lt} is the transmission power loss at time t in megawatts. P_{Lt} is calculated using the B-Matrix loss coefficients and the general form of the loss formula using B-coefficients is:

$$P_{Lt} = \sum_{i=1}^{N}\sum_{j=1}^{N} P_{it} B_{ij} P_{jt} \quad (5)$$

2. *Real power generation limit:*

$$P_{i\min} \le P_{it} \le P_{i\max} \quad (6)$$

where P_{imin} is the minimum limit, and P_{imax} is the maximum limit of real power of the i^{th} generating unit in megawatts.

3. *Generating unit ramp-rate limits:*

$$\begin{aligned} P_{it} - P_{i(t-1)} &\le UR_i, \quad i = 1, ..., N \\ P_{i(t-1)} - P_{it} &\le DR_i, \quad i = 1, ..., N \end{aligned} \quad (7)$$

where UR_i and DR_i are the ramp-up and ramp-down limits of i^{th} generating unit in megawatts. Thus, the constraint of Equation 7 due to the ramp-rate limits is modified as

$$\max(P_{i\min}, P_{i(t-1)} - DR_i) \le P_{it} \le \min(P_{i\max}, P_{i(t-1)} + UR_i) \quad (8)$$

such that;

$$P_{it,\min} = \max(P_{i\min}, P_{i(t-1)} - DR_i) \quad \text{and} \qquad (9)$$
$$P_{it,\max} = \min(P_{i\max}, P_{i(t-1)} + UR_i)$$

4. *Constraint satisfaction technique:*

To satisfy the equality constraint of Equation 4, a loading of any one the units is selected as the depending loading P_{Nt}. The power level of N[th] generator is given by:

$$P_{Nt} = P_{Dt} + P_{Lt} - \sum_{i=1}^{(N-1)} P_{it} \qquad (10)$$

The transmission loss P_{Lt} is function of all the generators including that of dependent generator, and it is given by:

$$P_{Lt} = \sum_{i=1}^{(N-1)} \sum_{j=1}^{(N-1)} P_{it} B_{ij} P_{jt} + 2P_{Nt}\left(\sum_{i=1}^{(N-1)} B_{Ni} P_{it}\right) + B_{NN} P_{Nt}^2 \qquad (11)$$

Expanding and rearranging, Equation 11 becomes:

$$B_{NN} P_{Nt}^2 + \left(2\sum_{i=1}^{(N-1)} B_{Ni} P_{it} - 1\right) P_{Nt} + \left(P_{Dt} + \sum_{i=1}^{(N-1)} \sum_{j=1}^{(N-1)} P_{it} B_{ij} P_{jt} - \sum_{i=1}^{(N-1)} P_{it}\right) = 0 \qquad (12)$$

The loading of dependent generator can be determined by solving Equation 12 using standard algebraic method.

5. *Emission constraint:*

Total emission of NOx from the system in the entire scheduling horizon should be just less than or equal to specified level

$$\sum_{t=1}^{T} \sum_{i=1}^{N} E_{it}(P_{it}) \le E_s \qquad (13)$$

where E_s is the specified emission limit.

3. OVERVIEW OF DIFFERENTIAL EVOLUTION

Differential Evolution developed by Storn and Price is one of the excellent evolutionary algorithms [13]. Differential evolution was developed in 1995 as a population-based stochastic evolutionary optimization algorithm. In the initialization, a population of *NP* vectors

$$X_i^G; \quad i = 1, 2, \ldots, NP \qquad (14)$$

is randomly generated within user–defined bounds. The size of the population is specified by the parameter *NP* that has to be set by the user. Usually it is kept fixed during an optimization run. The population members are real-valued vectors with dimension *D* that equals the number of decision variable in the optimization problem. For convenience, the decision vector, X_i^G, is represented as $(X_{1i}^G, X_{2i}^G, \ldots, X_{Di}^G)$. The fitness of each individual in the population is evaluated. The evolutionary operator's mutation, recombination and selection are applied to every population member to generate a new generation. First, a mutant vector is built by adding a vector differential to a population vector of individual according to the following Equation:

$$Z_i^{G+1} = X_i^G + F.(X_{r1}^G - X_{r2}^G) \qquad (15)$$

where *i = 1, 2,..., NP* is the individual's index of population; *G* is the generation; The mutation or scaling factor *F* is a control parameter of DE that has to be set by the user. The indexes r_1, r_2 represents the random and mutually different integers generated within the range [1, NP] and also different from the running index *i*. The specialty in DE lies in the mutation step whereby two vectors are randomly selected from the population and the vector difference between them is established. The difference is multiplied by a mutation factor, *F* and added to a third randomly chosen vector from the population. This step is known as differential variation and the result is known as mutant vector. The mutation factor controls the amplification of the difference between two individuals so as to avoid search stagnation and is usually taken from the range [0.1, 1]. DE is sensitive to the choice of mutation factor.

Following the mutation operation, recombination is applied to the population. Recombination is employed to generate a trial vector by replacing certain parameters of the target with the corresponding parameters of a randomly selected donor vector. In the recombination operation, each gene of the *i*[th] individual is reproduced from the mutant vectors $Z_i^{G+1} = (Z_{1i}^{G+1}, Z_{2i}^{G+1}, \ldots, Z_{Di}^{G+1})$ and the current individual $X_i^G = (X_{1i}^G, X_{2i}^G, \ldots, X_{Di}^G)$ as follows:

$$U_{ji}^{G+1} = \begin{cases} X_{ji}^G, & \text{if a random number} > CR \\ Z_{ji}^{G+1}, & \text{otherwise; } j = 1,2, \ldots D,\ i = 1, \ldots, NP \end{cases} \qquad (16)$$

where *CR* is a crossover or recombination rate in the range [0, 1] and has to be set by the user.

The selection operation selects according to the fitness value of the population vector and its corresponding trial vector, which vector will survive to be a member of the generation. If *f* denotes the objective function under minimization, then

$$X_i^{G+1} = \begin{cases} U_i^{G+1} & \text{if } f(U_i^{G+1}) < f(X_i^G) \\ X_i^G & \text{otherwise} \end{cases} \qquad (17)$$

In this case, the cost of each trial vector U_i^{G+1} is compared with that of its parent target vector X_i^G. If the cost *f*, of the target vector X_i^G is lower than that of the trial vector, the target is allowed to advance to the next generation. Otherwise, the target vector is replaced by the trail vector in the next generation. The mutation, recombination and selection are repeated for *NP* times to complete one iteration.

The above iterative process of mutation, recombination and selection on the population will continue until a user-specified stopping criterion is met.

4. OPPOSITION-BASED SELF-ADAPTIVE DIFFERENTIAL EVOLUTION ALGORITHM FOR ECDED PROBLEM

The detailed implementation of the developed algorithm for ECDED problem is given below:

1. Opposition-based population initialization:

DE uses *NP* D-dimensional parameter vectors:

$$P_{ok,G}\ ;\quad k = 1,\ 2,\ ...,\ NP \tag{18}$$

in a generation *G*, with *NP* being constant over the entire optimization process. At the start of the procedure, that is, generation *G=1*, the population vectors have to be generated randomly within the limits. For *T* intervals in the generation scheduling horizon, there are *T* dispatches of generation by *N* generating units. An array of control variable vectors or positions of the each agent can be represented as:

$$P_{0k,G} = \left[(P_{011}\ P_{021}\ \cdots P_{0N1})\ \cdots (P_{01T}\ P_{02T}\ \cdots P_{0NT})\right], \quad \text{for } k = 1, 2, 3, ..., NP \tag{19}$$

where P_{0NT} is the generation power output of the N^{th} unit at T^{th} interval. Opposite population vectors are represented as:

$$OP_{k,G} = (OP_{11}\ OP_{21}\ \cdots OP_{N1})\ \cdots (OP_{1T}\ OP_{2T}\ \cdots OP_{NT}) \tag{20}$$

Opposite population vectors are generated by

$$OP_{k,G} = a_j + b_j - P_{oi,j} \quad i = 1, 2, ..., NP,\ \ j = 1, 2, ..., D,\quad k = 1,\ 2,\ 3, ..., NP \tag{21}$$

where $P_{oi,j}$ denote j^{th} variable of i^{th} vector of randomly generated initial population. a_j and b_j are range of the j^{th} variable. *NP* fittest individuals are selected from the set {P_0, OP} as an initial population *P*.

$$P_{k,G} = \left[\left(P_{k1}\ P_{k2}\ P_{k3} \cdots P_{kD}\right)\right],\ \text{ for } k = 1, 2, 3, ..., NP \tag{22}$$

2. Mutation process:

Mutation is an operation that adds a vector differential to a population vector of individuals. For the following generation *G+1*, new vectors $V_{k,G+1}$ are generated according to the following mutation scheme

$$V_{k,\,G+1} = P_{k,\,G} + F_{k,G}\cdot(P_{r1,\,G} - P_{r2,\,G}), \quad \text{for } k = 1, 2, 3, ..., NP \tag{23}$$

The integers r_1 and r_2 are chosen randomly over [*1*, *NP*] and should be mutually different from the running index *k*. Under certain circumstances, the index *k* will be exchanged by an arbitrary random number r_3 ε [*1*, *NP*]. *F* is a scaling factor which controls the amplification of the differential variation. A self-adaptive control mechanism is used to change the control parameter *F* during the run. At generation *G*=1, the scaling factor *F* for each individual in the population vector are randomly generated within the range [0.1, 1.0]. The scaling factor for each vector in the population at generation *G* is represented by:

$$F_{k,G} = \left(F_{1,G}\ F_{2,G}\ F_{3,G} \cdots F_{NP,G}\right) \tag{24}$$

The new control parameters $F_{k,G+1}$ for subsequent generation were calculated as follows:

$$F_{k,G+1} = \begin{cases} F_l + rand_1 * F_u & \text{if } rand_2 < \tau_1 \\ F_{k,G}, & \text{otherwise} \end{cases} \quad \text{for } k = 1,\ 2,\ ...\ ,\ NP \tag{25}$$

This scheme provides for automatic self-adaptation and eliminates the need to adapt standard deviations of a probability density function. rand are uniform random values within the range [0, 1.0]. τ_1 represent probability to adjust control parameter *F*. F_l, F_u and τ_1, are taken fixed values of 0.1, 0.9 and 0.8 respectively. The scaling factor *F* is varied randomly within a specified range during the evolutionary process. The range of *F* is determined by values F_l and F_u. If control parameter *F* is equal to zero, the new trial vector is generated using crossover operation but not mutation. Therefore F_l value is set equal to 0.1 and F_u value is set equal to 0.9. Hence the new scaling factor $F_{k,\ G+1}$ calculated from Equation 25 takes a value from 0.1 to 1.0 in a random manner. The range of probability τ lies between 0 and 1. The probability τ_1 of changing scaling factor *F* is chosen as 0.8, because higher value of τ increases the probability of utilizing better control parameters during the optimization process. The encoding aspect of scaling factor is shown in Table 1.

Table 1. Self-adapting: encoding aspect.

$P_{1,G}$	$F_{1,G}$
$P_{2,G}$	$F_{2,G}$
$P_{3,G}$	$F_{3,G}$
...	...
$P_{NP,G}$	$F_{NP,G}$

3. Crossover operation:

Each gene of i^{th} individual is replaced from the mutant vectors $V_{K,G+1}$ and the present individual $P_{K,G}$. That is:

$$U_{k,\,G+1} = P_{k,\,G} \times (1 - CR_{k,G+1}) + V_{k,\,G+1} \times CR_{k,G+1};\quad \text{for } k = 1,\ 2,\ ...,\ NP \tag{26}$$

The crossover factor $CR_{k,G}$ is randomly taken from the interval [0, 1] for each individual vector in the initial population. New crossover factor $CR_{k,G+1}$ for each individual during evolution process are calculated by

$$CR_{k,(G+1)} = \begin{cases} CR_l + rand_3 * CR_u & \text{if } rand_4 < \tau_2 \\ CR_{k,G} & \text{otherwise} \end{cases} \tag{27}$$

τ_2 represent probability to adjust control parameter *CR*. CR_l, CR_u, τ_2 are taken fixed values of 0.1, 0.9 and 0.8 respectively. The new crossover factor $CR_{k,G+1}$ calculated from Equation 27 takes a value between 0 and 1 by setting CR_l equal to 0.1 and CR_u equal to 0.9. The best values of control parameters $CR_{k(G+1)}$ are obtained by setting the probability τ_2 equal to 0.8.

4. *Evaluation of each agent:*

Each individual in the population is evaluated using the fitness function of the problem to minimize the fuel cost and emission functions. The first generator of the sample system can be treated as dependent generator. The real power limit of the first generator and the unit ramp-rate limits are constrained by adding them as a exact penalty term to the objective function to form a generalized fitness function f_k as given below

$$f_k = W_1 * \sum_{t=1}^{T}\sum_{i=1}^{N} F_{it}(P_{it}) + W_2 * \sum_{t=1}^{T}\sum_{i=1}^{N} E_{it}(P_{it}) + \sum_{t=1}^{T} \mu_1 |P_{1t} - P_{1t\lim}| + \sum_{t=2}^{T}\sum_{i=2}^{N} \mu_r |P_{it} - P_{r\lim}| \quad (28)$$

where μ_1 and μ_r are penalty parameters, and

$$P_{1t\lim} = \begin{cases} P_{1\min,} \text{ if } P_{1t} < P_{1\min} \\ P_{1\max,} \text{ if } P_{it} > P_{1\max} \\ P_{1t,} \quad otherwise \end{cases} \quad (29)$$

$$P_{r\lim} = \begin{cases} P_{i(t-1)} - DR_i, & \text{if } P_{it} < P_{i(t-1)} - DR_i \\ P_{i(t-1)} + UR_i, & \text{if } P_{it} > P_{i(t-1)} + UR_i \\ P_{it,} & otherwise \end{cases} \quad (30)$$

The penalty terms associated with inequality constraints are added to the objective function. The penalty terms reflect the violation of the constraints and assign a high cost of the penalty function to candidate point far from the feasible region.

5. *Estimation and selection:*

The parent is replaced by its child if the fitness of the child is better than that of its parent. Explicitly, the parent is retained in the next generation if the fitness of the child is worse than that of its parent. DE selection scheme is based on local competition only, i.e. a child $U_{k,G+1}$ will compete against one population member $P_{k,G}$ and survivor will enter the new population. The number NT of children which may be produced to compete against $P_{k,G}$ should be chosen sufficiently high so that sufficient number of child will enter the new population. if $U_{k,G+1}$ is worse than that of its parent , the vector generation process defined by Equations 23 and 26 is repeated up to NT times. If $U_{k, G+1}$ still worse than that of its parent, $P_{k,G+1}$ will be set to $P_{k, G}$. An insufficient number NT leads to survival of too many old population vectors, which may induce stagnation. To prevent a vector $P_{k,G}$ from surviving indefinitely, DE employs the concept of aging. NE defines how many generations a population vector may survive before it has to be replaced due to excessive age. To this end $P_{k,G}$ in Equation 22 is checked first for how many generations it has already lived. If $P_{k,G}$ has an age of less than NE generations it remains unaltered, otherwise $P_{i,G}$ is replaced by $P_{r3,G}$ with r_3 not equal to k being a randomly chosen integer r_3 ε [1, NP]. In short, if $P_{k,G}$ is too old, it may not serve as a parent vector any more but will be replaced by a randomly chosen member of the current generation G.

6. *Opposition-based generation jumping:*

In this approach, the evolutionary process is forced to jump to a new solution candidate, which ideally is fitter than the current one. Based on a jumping rate J_r, (that is, jumping probability) after generating new populations by mutation, crossover, and selection, the opposite population is calculated, and the *NP* fittest individuals are selected from the union of the current population and the opposite population. Generation jumping calculates the opposite of each variable based on minimum and maximum values of that variable in the current population.

7. *Stopping criterion:*

The procedure from 2 to 6 is repeated until the maximum number of iterations reached.

5. SOLUTION METHODOLOGY

The overall procedure of the opposition-based self-adaptive differential evolution for ECDED problem can be summarized as follows:

Step 1. Read the system data.

Step 2. Assign the initial weighting factors W_1 and W_2 for fuel cost and emission objectives of ECDED problem.

Step 3. Initialize the population vector P_o randomly within the lower and upper generation limits of generating units.

Step 4. Generate the opposite population *OP* by applying an opposition-based learning scheme in the randomly generated population vectors P_o.

Step 5. Select the NP fittest individuals from the set $\{P_o, OP\}$ as an initial population P.

Step 6. Evaluate the fitness of each vector in the population.

Step 7. Generate a new population where each candidate individual is generated in parallel according to mutation, crossover, and selection.

Step 8. Calculate the opposite population from the new population based on jumping rate J_r.

Step 9. Select the NP fittest individuals from the union of the new population and the opposite population.

Step 10. Loop to Step 4, until predefined maximum number of iterations reached.

Step 11. Check the emission constraint

$$\sum_{t=1}^{T}\sum_{i=1}^{N} E_{it}(P_{it}) \le E_s$$

if emission constraint is not satisfied, adjust the weighting factors of fuel cost and emission objectives and go to Step 3.

Step 12. Terminate the above iterative procedure.

6. SIMULATION RESULTS AND DISCUSSION

In order to assess the performance of the opposition-based self-adaptive differential evolution algorithm for ECDED problem, it has been applied to five-unit sample system with cost and emission characteristics exhibiting a non-smooth fuel cost and emission functions are considered. The cost and emission coefficients, generation limits, ramp-rate constraints, loss coefficients and load demand for 24 hours of sample system are given Appendix, which are taken from [12]. The DE based algorithm for emission constrained dynamic economic dispatch problem was implemented using Matlab 6.5 on a PC with a Pentium IV, 2.8 GHz processor. The control parameters chosen for the sample system are population size NP=200, maximum number of iterations NG=1000, number of trials per iteration NT=10, number of generations a population vector may survive before it has to be replaced due to excessive age NR=5, and jumping rate Jr = 0.6.

The trade-off curve between economic and emission objectives is evaluated by solving the emission-constrained dynamic economic dispatch using proposed algorithm by varying the weighting factor W_1 between 0 and 1. The weighting factors convert the bi-objective optimization problem into a single objective optimization problem. The minimum generation cost and maximum emission level of emission-constrained dynamic economic dispatch problem are obtained through the developed algorithm by fixing the weighting parameters W_1 equal to one and W_2 equal to zero, which gives the condition for minimum fuel cost of generation and maximum emission level. The optimal generation schedule which gives the maximum generation cost and minimum emission level are obtained by fixing the weighting parameters W_1 equal to zero and W_2 equal to one which gives the condition for minimum emission level and maximum cost of generation. The fuel and emission objectives can be controlled by adjusting the weighting parameters W_1 and W_2. The opposition-based self adaptive differential evolution approach for emission-constrained dynamic economic dispatch can be implemented to determine the value of trade-off parameters W_1 and W_2 at which the total emission is just less than the specified emission limit.

Table 2. Optimal generation schedule of dynamic economic dispatch (w_1=1, w_2=0).

Time (h)	P_1 (MW)	P_2 (MW)	P_3 (MW)	P_4 (MW)	P_5 (MW)	P loss (MW)
1	14.8095	98.0826	113.7231	137.0452	50.0196	3.6800
2	14.9972	98.9270	113.0434	160.4751	51.7393	4.1820
3	10.4523	99.2815	110.5302	208.0819	51.8180	5.1640
4	11.9181	99.1119	112.7698	210.5835	101.8019	6.1852
5	10.5002	98.6940	103.5708	209.8901	142.1480	6.8031
6	10.1690	104.5959	112.3377	210.0912	178.8157	8.0094
7	10.2115	96.1525	112.3206	212.8818	202.9120	8.4784
8	11.8496	98.8964	112.4297	210.2562	229.8335	9.2654
9	41.8310	98.5027	112.0982	217.9059	229.8741	10.2120
10	65.6715	98.9234	112.3600	208.0867	229.5145	10.5561
11	71.0421	105.5885	112.7478	209.8059	231.8705	11.0548
12	71.6327	115.5313	114.8405	218.3357	231.3665	11.7069
13	62.4404	97.4525	113.2729	208.6822	232.7110	10.5591
14	49.7905	98.7327	112.2857	209.1842	230.1770	10.1701
15	41.7571	98.8856	117.3047	175.6885	229.4390	9.0748
16	11.9744	101.3312	113.0138	131.1922	229.7226	7.2341
17	11.5820	98.6270	110.5702	124.8565	219.0461	6.6817
18	13.7859	93.9592	113.0043	165.8771	229.2975	7.9240
19	11.3137	99.3818	111.6471	209.9447	230.9870	9.2742
20	41.2393	107.9754	116.2899	210.2312	238.8878	10.6236
21	37.5408	99.2357	114.4409	209.8378	228.8425	9.8976
22	10.4702	100.1646	111.5458	211.5564	179.1895	7.9265
23	11.4301	105.6879	113.3066	162.8288	139.6807	5.9342
24	10.4203	86.6914	109.9842	121.7084	138.6988	4.5031

The dynamic economic dispatch result obtained through the proposed method is given in Table 2 and the minimum emission dispatch result is given in Table 3. The optimal dispatch of committed generating units obtained at weighting factors at W_1=0.5 and W_2= 0.5 are given in Table 4. The optimal generation schedule (in MW) given in Tables 2 to 4 satisfies the generator constraints and the load demand plus transmission losses in each interval of the scheduling horizon. The convergence characteristic of opposition-based self-adaptive differential evolution algorithm is given in Figure 1. The simulation results obtained for various weight factors using opposition-based differential evolution algorithm have been compared with the results obtained using particle swarm optimization method reported in [12]. From the Table 5, it is clear that when W_1 varies from 0 to 1 generation cost increases continuously but emission level decreases continuously. The fuel cost obtained through proposed approach for pure dynamic economic dispatch is 43849$ compared to 47,852$ of PSO method and total emission for pure emission dispatch is 17,992 (lb) compared to 19,094 (lb) of PSO method reported in [12]. Figure 2 shows the trade off curve plotted against total fuel cost and emission.

For the specified emission level of 20175 (lb), the proposed opposition-based self-adaptive algorithm has been applied to ECDED problem to find the optimal generation schedule which produces total emission just below the specified emission level by adjusting the weighting factors W_1 and W_2 in steps of 0.02 so as to achieve the minimum fuel cost with controlled emission. The optimal generation schedule (in MW) for the specified emission level of emission-constrained dynamic economic dispatch problem is given in Table 6, that gives the fuel cost of 45,033$ and emission of 20,165 (lb), which is just below the specified emission level and the corresponding weighting factors are W_1=0.48 and W_2= 0.52. The average computation time taken by the algorithm for different weighting factors is 4.23 minutes.

Table 3. Optimal generation schedule of minimum emission dispatch (w_1=0, w_2=1).

Time (h)	P_1 (MW)	P_2 (MW)	P_3 (MW)	P_4 (MW)	P_5 (MW)	Ploss (MW)
1	56.2654	57.0884	117.4247	119.1773	63.5133	3.4691
2	63.1614	55.2369	122.5385	100.4761	97.4475	3.8604
3	59.3409	71.9681	124.7083	133.0737	90.5551	4.6462
4	68.7330	88.2206	138.7872	133.2144	106.8368	5.7920
5	66.4201	89.7905	163.9430	138.1666	106.1068	6.4270
6	66.2125	97.2322	163.5950	177.1908	111.4551	7.6857
7	70.6295	87.9900	166.4578	183.7193	125.3158	8.1124
8	71.2219	101.2328	159.6436	181.0833	149.6808	8.8623
9	70.9401	117.1887	174.3348	194.7316	142.7309	9.9261
10	71.2130	115.9100	166.3368	199.6096	161.2634	10.3329
11	71.1010	117.0058	174.7215	208.7548	159.2354	10.8186
12	71.3204	120.7789	174.9990	210.4358	173.8984	11.4324
13	70.5742	113.4659	174.8817	205.7224	149.6920	10.3361
14	70.7381	121.2539	174.1682	183.9385	149.8144	9.9132
15	70.5258	110.2789	173.1343	186.1666	122.8078	8.9135
16	68.7379	95.2374	156.6122	168.0502	98.3637	7.0014
17	70.7853	85.7097	139.9705	154.0308	113.9328	6.4291
18	71.1004	95.4525	166.5646	158.4588	124.0569	7.6332
19	70.5127	100.7193	174.3128	182.1679	135.1489	8.8616
20	70.1437	119.2889	171.1080	204.8644	148.9545	10.3595
21	70.8418	110.4890	174.0827	196.8726	137.3467	9.6328
22	70.4696	97.7109	144.5786	182.7344	117.1382	7.6316
23	66.5272	76.8006	133.0156	150.3484	106.0359	5.7276
24	57.0801	58.3239	129.2007	133.8823	88.9123	4.3993

Table 4. Optimal generation schedule of combined dynamic economic and emission dispatch (w_1=0.5, w_2=0.5).

Time (h)	P_1 (MW)	P_2 (MW)	P_3 (MW)	P_4 (MW)	P_5 (MW)	Ploss (MW)
1	26.0516	99.5928	112.7761	125.1264	50.0842	3.6312
2	16.7775	98.2528	112.8123	124.8851	86.2929	4.0206
3	12.4134	94.3960	112.1398	124.6751	136.1269	4.7512
4	42.3932	98.4898	113.0815	142.1870	139.7110	5.8625
5	35.8226	98.7052	130.1449	160.0377	139.7902	6.5007
6	55.6768	98.1897	112.6778	209.5924	139.7287	7.8653
7	70.7257	98.6679	114.5558	210.1262	140.2361	8.3116
8	70.7781	107.1409	123.7421	209.7805	151.6000	9.0415
9	70.9460	107.5942	112.5017	209.7503	199.3276	10.1198
10	65.6928	98.5185	112.5277	209.8310	227.9857	10.5557
11	72.0481	102.0320	116.9607	211.3345	228.6450	11.0203
12	71.8599	102.6370	126.6377	220.7283	229.7500	11.6129
13	70.9563	99.0133	112.6088	206.0731	225.8877	10.5393
14	50.8889	98.4904	112.1312	209.6104	229.0463	10.1673
15	70.4956	98.5579	112.6937	159.6394	221.6448	9.0314
16	71.8869	98.8996	112.6701	124.8475	178.7273	7.0314
17	71.1463	98.6381	113.0285	142.2645	139.4026	6.4801
18	70.8787	98.6762	113.4308	192.2328	140.5734	7.7919
19	70.9653	98.7463	115.4822	208.6504	169.2014	9.0456
20	71.8591	100.2897	113.6500	209.7636	218.9706	10.5329
21	72.4357	98.7192	114.1106	175.4529	229.0666	9.7850
22	71.9374	98.9381	135.6864	125.5746	180.4608	7.5973
23	41.9785	98.3295	112.2908	140.5840	139.6137	5.7965
24	11.9886	90.5298	111.3470	123.2329	130.4078	4.5061

Table 5. Comparison of fuel cost and emission objective functions with PSO method.

Weights		PSO Method [12]		Proposed Method	
W_1	W_2	Fuel cost ($)	Emission (lb)	Fuel cost ($)	Emission (lb)
1.0	0.0	47852	22405	43849	23022
0.8	0.2	50124	21802	44442	22237
0.5	0.5	50893	20163	44967	20466
0.2	0.8	52047	20035	48636	18272
0.0	1.0	53086	19094	52347	17992

Table 6. Optimal generation schedule of emission-constrained dynamic economic dispatch (w_1=0.48, w_2=0.52).

Time (h)	P_1 (MW)	P_2 (MW)	P_3 (MW)	P_4 (MW)	P_5 (MW)	P loss (MW)
1	15.9856	20.8843	112.5146	124.9475	139.1360	3.4679
2	12.2198	49.0128	112.6367	125.2050	139.8389	3.9132
3	28.7822	72.3547	113.3437	125.1337	140.0458	4.6601
4	58.6233	98.9758	113.3404	124.9853	139.9108	5.8357
5	71.3906	98.6138	114.9793	140.2076	139.2822	6.4736
6	70.8220	100.4053	114.3266	190.1285	140.1050	7.7874
7	70.5681	99.2961	113.1395	211.1023	140.2165	8.3224
8	70.8784	101.9631	122.4867	211.4912	156.2165	9.0358
9	71.5777	98.6052	113.6158	210.6021	205.7009	10.1017
10	63.5507	99.6994	112.8857	208.8088	229.6143	10.5589
11	72.0622	99.7723	119.2898	209.9828	229.8950	11.0022
12	71.4697	98.2784	142.3658	209.8747	229.5157	11.5044
13	67.7437	98.5421	112.3142	209.4280	226.5235	10.5514
14	71.2510	98.1541	142.6741	209.6722	178.2074	9.9588
15	64.5486	98.4480	112.3246	159.6850	228.0438	9.0499
16	71.9714	98.7654	112.7553	125.1865	178.3516	7.0302
17	68.6676	98.2865	112.5163	144.9778	140.0345	6.4828
18	69.5709	98.4063	113.1160	194.9778	139.7305	7.8015
19	70.9664	105.5751	119.6877	209.7752	157.0459	9.0503
20	71.5721	100.4992	125.8431	210.6314	205.9122	10.4580
21	71.0400	124.4544	116.9678	212.1722	165.2222	9.8565
22	48.8391	99.1083	113.9368	209.8532	141.0606	7.7980
23	18.8721	98.5554	112.8401	170.1933	132.5460	5.9088
24	10.1595	97.9892	112.0978	124.6402	122.6485	4.5351

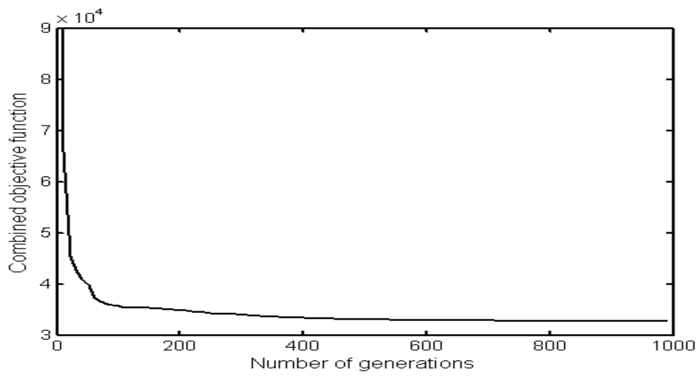

Fig. 1. Convergence characteristic of combined economic and emission objective functions (w_1=0.5, w_2=0.5).

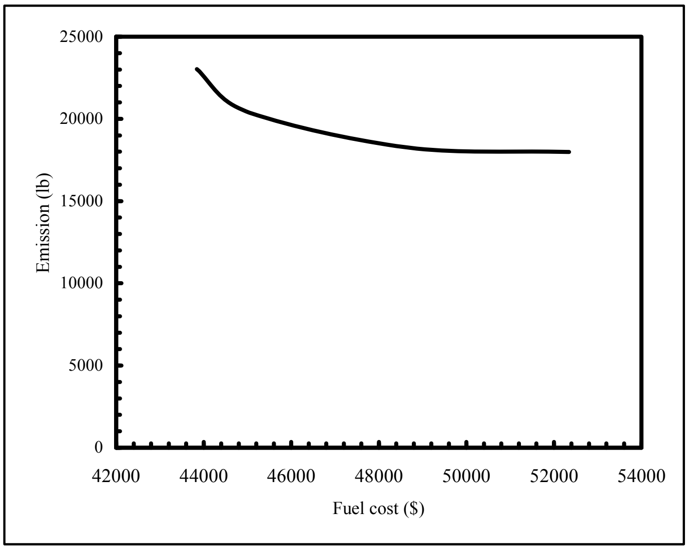

Fig. 2. Trade-off curve between fuel cost and emission.

7. CONCLUSION

A novel DE based approach for the solution of emission-constrained dynamic economic dispatch has been developed in this paper. The self-adaptive scheme introduced in the algorithm automatically adjusts its control parameter values during evolution process, which avoids the complication of tuning control parameters for heavily constrained optimization problem like ECDED problem. The opposition-based learning for population initialization and for generation jumping is utilized to accelerate the convergence of the proposed DE algorithm. The applicability of the algorithm for solving emission-constrained dynamic economic dispatch problem is represented on five-unit sample system. The comparison of the results with PSO method reported in the recent literature shows the superiority of the proposed method and its potential for solving nonlinear emission-constrained dynamic economic problem in a power system.

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APPENDIX

Appendix I: Cost coefficients and generation limits for 5-unit system

Quantities	Unit 1	Unit 2	Unit 3	Unit 4	Unit 5
a (\$/(MW)^2 h)	0.0080	0.0030	0.0012	0.0010	0.0015
b (\$/MWh)	2.0	1.8	2.1	2.0	1.8
c (\$/h)	25	60	100	120	40
e (\$/h)	100	140	160	180	200
f (1/MW)	0.042	0.040	0.038	0.037	0.035
P_{min} (MW)	10	20	30	40	50
P_{max} (MW)	75	125	175	250	300
UR (MW/h)	30	30	40	50	50
DR (MW/h)	30	30	40	50	50

Appendix II: Emission coefficients for 5-unit system

Quantities	Unit 1	Unit 2	Unit 3	Unit 4	Unit 5
α (lb/(MW)^2 h)	0.0180	0.0150	0.0105	0.0080	0.0120
β (lb/MWh)	-0.805	-0.555	-1.355	-0.600	-0.555
γ (lb/h)	80	50	60	45	30
η (lb/h)	0.6550	0.5773	0.4968	0.4860	0.5035
δ (1/MW)	0.02846	0.02446	0.02270	0.01948	0.02075

Appendix III: Transmission loss coefficients for 5-unit system

$$B = \begin{bmatrix} 0.000049 & 0.000014 & 0.000015 & 0.000015 & 0.000020 \\ 0.000014 & 0.000045 & 0.000016 & 0.000020 & 0.000018 \\ 0.000015 & 0.000016 & 0.000039 & 0.000010 & 0.000012 \\ 0.000015 & 0.000020 & 0.000010 & 0.000040 & 0.000014 \\ 0.000020 & 0.000018 & 0.000012 & 0.000014 & 0.000035 \end{bmatrix} \quad per\ MW$$

Appendix IV: Load demand for 24 hours

Time (h)	Load (MW)	Time (h)	Load (MW)	Time (h)	Load (MW)	Time (h)	Load (MW)
1	410	7	626	13	704	19	654
2	435	8	654	14	690	20	704
3	475	9	690	15	654	21	680
4	530	10	704	16	580	22	605
5	558	11	720	17	558	23	527
6	608	12	740	18	608	24	463