IJNRD.ORG ISSN : 2456-4184
INTERNATIONAL JOURNAL OF NOVEL RESEARCH AND DEVELOPMENT (IJNRD) | IJNRD.ORG
An International Open Access, Peer-reviewed, Refereed Journal

Reserve Constrained Non-Linear, Non-Convex Power Economic Dispatch With Prohibited Operating Zones, Ramp Rates, Valve Point Loading Effects and Transmission Losses

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Abstract: This paper presents a novel stochastic optimization approach to determining the feasible optimal solution of the power economic dispatch (PED) problem considering various generator constraints. Many practical constraints of generators, such as ramp rate limits, prohibited operating zones and the valve point effects are considered. These constraints make the PED problem a non-convex minimization problem with constraints. The proposed shuffled differential evaluation (SDE) utilizes the concept of the shuffled frog – leaping algorithm in the original differential evaluation to accelerate the search for the global optimum. A typical 13-unit power system is considered to evaluate and compare the performance of the proposed SDE algorithm with those methods reported in the literature. Numerical results indicate that the performance of the proposed algorithm outperforms the methods reported in the literature.

Index Terms **- Power economic dispatch, prohibited operating zones, shuffled differential evaluation.**

I. INTRODUCTION

An important optimization task in power system operation is the power economic dispatch (PED) in which generation is allocated among the committed units. The objective of PED is to minimize the total generation cost of units, while satisfying the various equality and inequality constraints. Physically, a generating unit may have prohibited operating zones between the minimum and maximum power outputs. The generators that operate in these prohibited zones may experience amplification of vibrations in their shaft bearings. Hence, these vibrations should be avoided in practical application. Since the unit generation output cannot be changed instantaneously, the unit in the actual operating processes is restricted by its ramp rate limit [1-3]. Moreover, the units of real input–output characteristics include higher order nonlinearities and discontinuities owing to the valve point effects and piecewise quadratic cost functions. The valve point effects have been modeled as a circulating commutated sinusoidal component in the cost function [4-5].

Also one of the most important duties of the system operator with regards to maintaining power system security and reliability is to monitor system operating reserve and its ability to respond to disturbances within the system [6]. Scheduling sufficient reserve capacity helps power systems to overcome unscheduled generator outages and major load forecast errors without load shedding. The PED problem with the above considerations is usually a non-smooth/non-convex optimization problem [3].

This kind of optimization problem is very hard, if not impossible, to solve using traditionally deterministic optimization algorithms. Several classical techniques have been used for solving the economic dispatch problems. The Lagrangian multiplier method [7], which is generally used for solving the PED problem, is not directly applicable. To solve the non-smooth/non-convex PED problems, Lee and Breipohl [3] decomposed the non-convex decision space into a number of convex sub-regions and then used the Lagrangian multiplier method to solve the problem. The drawback of this approach is the large computational burden to obtain an optimal solution when a system has several units with prohibited zones. Fan and McDonald [8] proposed an algorithm based on conventional l–d iterative dispatch to obtain the solution. In the recent past, several evolutionary computational intelligence techniques have been used for solving the non-smooth/non-convex economic dispatch problems. Su and Chiou [9] applied the Hopfield network technique for solving the PED problem with prohibited operating zones, but the Hopfield network method requires two-phase computations and was not able to consider power loss. Lin et al. [10] presented integrated evolutionary programming, tabu search (TS) and quadratic programming (QP) methods to solve non-convex PED problems. This integrated artificial intelligence method also requires two-phase computations.

Lin et al. [11] developed an improved TS algorithm for PED with non-smooth cost functions by relaxing the prohibited zones and system spinning reserve. Sewtohul et al. [12] proposed genetic algorithms (GAs) to solve the PED problem in light of the valve point effect. Wong and Fung [13] developed a simulated annealing based PED algorithm to solve PED considering the transmission loss. Sinha et al. [14] used an evolutionary programming (EP) method to solve PED problems. However, the last two studies did not consider the prohibited zones. Gaing [15-16] proposed a particle swarm optimization (PSO) method for solving the PED problems in power systems.

Recently, powerfull evolutionary optimization algorithm such as differential evolution (DE) techniques developed by Storn and Price [17], which is simple, easy to implement, and significantly faster is employed for power system optimization problems. It has been demonstrated in the literature [18-22] that the search ability of evolutionary optimization algorithms can be improved by the hybridization with local search. Such a hybrid algorithm has often been referred to as memetic algorithms [23]. Memetic algorithms are hybrid algorithms that combine both the evolutionary algorithms and local search techniques. For different classes of optimization problems, memetic algorithms have been proved to be much faster and more accurate than the evolutionary algorithms.

In this chapter, the shuffled differential evaluation algorithm [24-27] for solving the non-smooth/non-convex PED problems considering the various physical constraints is presented. The proposed SDE algorithm is applied on 13-unit PED systems from the literature to compare the performance of the proposed method with other stochastic optimization methods reported in the literature.

II. PROBLEM FORMULATION

The objective of the PED is to minimize the total generation cost of a power system over some appropriate period while satisfying various constraints. The power system balance of conditions for system demand, power losses and entire generator power, as well as the generating power constraints, including prohibited zones, ramp rate limit, spinning reserve and valve point effect for all units, should be satisfied. In this chapter, the maximum spinning reserve capacity is set at 15–30% of the maximum power. The valve point constraint has been modeled on either the piece-wise quadratic cost function or a commutated sinusoidal function to represent the valve point loading in the cost function. Therefore the PED problem considering generator constraints can be mathematically described as follows

$$\min \sum_{i \in \Psi} F_i(P_i)$$

$$\text{ie.,} \quad \min \sum_{i \in \Psi} (a_i P_i^2 + b_i P_i + c_i + | e_i \sin(f_i (P_{i,\min} - P_i)) |) \qquad (1)$$

where i denotes index of units, F_i, fuel cost function of unit i; P_i, power generation of unit i; $P_{i,\min}$, minimum generation limit of unit i; Ψ is set of all units i.e., {1,2, . . , N}, N is number of generator units; a_i, b_i, c_i, e_i, and f_i, fuel cost coefficients of unit 'i'. Subject to the following constraints

(i) Power balance constraint

$$\sum_{i \in \Psi} P_i = P_D + P_{loss} \qquad (2)$$

$$P_{loss} = \sum_{i=1}^{N} \sum_{j=1}^{N} P_i B_{ij} P_j + \sum_{i=1}^{N} B_{0i} P_i + B_{00} \qquad (3)$$

where P_D denotes total load demand; P_{loss}, power losses; B_{ij}, power loss coefficient.

(ii) System spinning reserve constraints

$$\sum_{i \in \Psi} S_i \geq S_R \qquad (4)$$

$$S_i = \min \{(P_{i\max} - P_i), S_{i,\max}\} \quad \forall i \in (\Psi - \psi) \qquad (5)$$

$$S_i = 0 \quad \forall i \in \psi \qquad (6)$$

where S_i, spinning reserve of unit i; S_R, system spinning reserve requirement; $P_{i,\max}$, maximum generation limit of unit i; $S_{i,\max}$, maximum spinning reserve of unit i; ψ, set of all units with prohibited zones. In a unit with prohibited operating zones, these zones strictly limit the unit's ability to regulate system load because load regulation may result in its falling into certain prohibited operating zones. Therefore the system spinning reserve requirement must be supplied by way of regulating the units without prohibited zones only.

iii) Generation limits of units

Ramp rate limits constraints

$$\max(P_{i\min}, P_i^0 - DR_i) \leq P_i \leq \min(P_{i\max}, P_i^0 + UR_i) \qquad (7)$$

Units with prohibited operating zones

$$\begin{cases} P_{i,\min} \leq P_i \leq P_{i,1}^l \\ or\ P_{ij-1}^u \leq P_i \leq P_{ij}^l, \quad j = 2,..., pz_i \\ or\ P_{in_i}^u \leq P_i \leq P_{i,\max} \quad \forall i \in \psi \end{cases} \qquad (8)$$

Units without prohibited operating zones

$$P_{i,\min} \leq P_i \leq P_{i,\max} \qquad (9)$$

where P_i^0, previous output power of unit *i*; UR_i, up ramp limit of unit *i*; DR_i, down ramp limit of unit *i*; P_{ij}^l, lower bound of the *j*th prohibited zone of unit i; P_{ij}^u; upper bound of the *j*th prohibited zone of unit *i*; pz_i, number of prohibited zones in unit *i*.

In this study, the treatment of constraints is performed with the penalty function methods. The penalty function methods are among the most popular techniques used to handle constraints, are easy to implement and are considered efficient. The penalty method is usually a close degree to the nearest solution in a reasonable region, and it can allow an objective function effort to arrive at the optimum solution. The penalty method is implemented in this chapter as follows.

When the PED takes account of the prohibited zone constraints, the delimitation point divides the prohibited zone into two sub-zones, that is the left and right prohibited subzones The delimitation point is set in the middle point of each prohibited zone in this work. When a unit operates in one of the prohibited zones, the strategy is to force the unit to move either towards the lower bound of that zone from the left sub-zone or towards the upper bound of that zone from the right sub-zone. The unit power must confirm to the constraint of (8) when the unit does not include prohibited zones. In addition to prohibited zone constraints, the computation results also must confirm to ramp rate limits in (7), the system spinning reserve requirement in (4) and the power balance condition in (2). The fuel cost function with these constrains is rewritten from (1) as follows

$$\min_{P_i} M = \sum_{i \in \Psi} F_i(P_i) + q_1 \left| \sum_{i \in \Psi} P_i - P_D - P_L \right| + q_2[\max(0, S_R - \sum_{i \in \Psi} S_i)] + \text{H1(Pi)} \tag{10}$$

where q1, and q2 are penalty factors when these terms are zero in (10), and no constraints are violated; otherwise, these terms are positive values. To solve the above mentioned system, the SDE is described as follows.

III. SHUFFLED DIFFERENTIAL EVOLUTION

Differential evolution (DE) may occasionally stop proceeding toward the global optimum even though the population has not converged to a local optimum even new individuals may enter the population, but the algorithm does not progress by finding any better solutions. This situation is usually referred to as stagnation. DE also suffers from the problem of premature convergence, where the population converges to some local optima of a multimodal objective function, losing its diversity.

SFLA simple, efficient memetic algorithm but only the worst frog in the memeplex adjusts its position using frog leaping rule with memeplex best or global best. It is an insufficient learning mechanism for the swarm, especially that the better frogs have fewer learning chances, unless that the worse catches up them. In order to utilize both the properties of DE and SFLA, a novel technique called shuffled differential evolution (SDE) has been developed with novel mutation operator for solution of complex optimization problems such as non-convex PED.

The proposed algorithm is based on shuffling property of SFLA and DE algorithm. Like other evolutionary algorithm, in SDE population is initialized as $[X_1, X_2, ...X_P]$ of *P* solutions, where *P* represents the population size. Each solution is represented as $X_i = [x_{1,i}, x_{2,i} ..., x_{N,i}]$ for *N*-dimensional problem. Fitness is calculated while satisfying constraints and population is sorted in descending order of their fitness and partitioned into memeplexes.

Unlike SFLA, within each memeplex all the frogs participate in the evolvement and has local search due to memetic evolution with DE operations such as mutation, crossover and selection, and global exploration due to the shuffling property of SFLA. This gives an edge to the proposed algorithm over other techniques, while finding global optimal solution. In SDE algorithm a novel mutation, DE/Memeplexbest/2 is performed for each frog of memeplex in the memetic evolution. After certain number of predefined memetic evolutions all frogs with their fitness are collected from each memeplex and shuffled. This process is repeated for specified number of generations.

3.1 Memetic evolution step of SDE

The proposed SDE uses shuffling property of SFLA and the memetic evolution step of SFLA is replaced by a differential evolution steps such as “DE/memeplexbest/2” mutation operation and followed by crossover and selection operations.

Pseudo code of the Shuffled Differential Evolution (SDE)

Begin*;*
Initialize the SDE parameters
Randomly generate a population of solutions (frogs);
For *k = 1 to SI;*
For each individual (frog); calculate fitness of ith frog;
Sort the population in descending order of their fitness;
Determine the global best frog;
Divide population into m memeplexes;
*/*memetic evolution step*/*
For *im=1 to m;*
For *ie=1 to IE*
Determine the best frog;
For *each frog*
Generate new donor vector (frog) with memeplex best/2 mutation operation

Apply crossover
Evaluate the fitness of new frog;
***If** new frog is better than old*
Replace the old with new one
End if
End for
End for
End for
*/*end of memetic evolution step*/*
Combine the evolved memeplexes;
Sort the population in descending order of their fitness;
Update the global best frog;
End for
End

3.2 "DE/Memeplexbest/2" Mutation

The general convention used for naming the various mutation strategies is DE/x/y/z, where DE stands for differential evolution, x represents a string denoting the vector to be perturbed, y is the number of difference vectors considered for perturbation of x, and z stands for the type of crossover being used. A new variant of the DE mutation scheme is proposed which is similar to "Scheme DE2". To combine the exploration and exploitation capabilities of DE, a hybrid mutation scheme is propose based on memeplex best that utilizes an explorative and an exploitive mutation operator, with an objective of balancing their effects. The explorative mutation operator has a greater possibility of locating the minima of the objective function. On the other hand, the exploitative mutation operator rapidly converges to a minimum of the objective function. In memeplex evolution step SDE creates a donor vector V_i corresponding to each population member or target vector X_i through mutation

"DE/memplexbest/2": $V_i = X_b + F \cdot (X_{r1} - X_{r2}) + F \cdot (X_{r3} - X_{r4})$ (11)

where *r1,r2,r3,* and *r4* are integers randomly chosen from the range 1 to *n*, where *n* is number of frogs in each memeplex, and all random numbers are different from the running index *i*. These indices are randomly generated once for each donor vector. The scaling factor *F* is a positive control parameter for scaling the difference vectors and X_b represents memeplex best frog.

Crossover: To increase the potential diversity of the population in SDE, same kind of DE crossover schemes are used here. The DE algorithm can use two kinds of crossover schemes—*exponential* and *binomial*. In the binomial crossover operation, the donor vector V_i exchanges its components with the target vector X_i to form the trial vector $U_i = [u_{1,i}, u_{2,i}, ...u_{N,i}]$ according to the following equation.

$$u_{j,i} = \begin{cases} v_{j,i} & \text{if } \text{rand} \le \text{CR or } j = j_{\text{rand}} \\ x_{j,i} & \text{otherwise} \end{cases} \quad (12)$$

where *CR* is crossover rate and rand is a uniformly distributed random number between 0 and 1, j_{rand} randomly chosen index in the range [1,*N*] and see that at least one component from V_i.

Selection: Selection operation is performed to keep the population size constant over subsequent generations. This procedure is same as in DE, used among the set of trial vector and the updated target vector to choose the best based on fitness. Selection as per the following equation:

$$X_i^{new} = \begin{cases} U_i & \text{if } f(U_i) \ge f(X_i) \\ X_i & \text{if } f(U_i) < f(X_i) \end{cases} \quad (13)$$

3.3 Parameters of SDE

Like all heuristics, parameter selection is critical to SDE performance. The important parameters are the number *m* of memeplexes, the number *n* of frogs in a memeplex, the number *IE* of evolution or infection steps in a memeplex between two successive shuffling and cross over rate *CR*, and scaling factor *F*. Based on experience, the population size *P* in general, is the most important parameter. An appropriate value for *P* is related to the complexity of the problem. The probability of locating the global optima increases with increasing population size. However, as the population size increases, the number of function evaluations to reach the goal increases, hence making it more computationally burdensome. The important parameters of SDE algorithm are given in **Table 1**.

In addition, when selecting *m*, it is important to make sure that *n* is not too small. If there are too few frogs in each memeplex, the advantage of the local memetic evolution strategy is lost. The other parameter, *IE*, can take any value greater than 1. If *IE* is small, the memeplexes will be shuffled frequently, reducing idea exchange on the local scale. On the other hand, if *IE* is large, each memeplex will be shrunk into a local optimum. The global optimum searching capability and the convergence speed are very sensitive to the choice of control parameters *F*, and *CR*. Proper values of *F* and *CR* are chosen in between 0 and 1.

Table 1
Description of SDE parameters

Parameter	Description

m	Number of memeplexes
n	Number of frogs in each memeplex
P	Population size
IE	Maximum number of internal evolutions
F	Scaling factor
CR	Crossover rate
SI	Maximum number of generations (number of shuffled iterations)

3.4 SDE Algorithm for PED Problem

In this section, a new approach, SDE algorithm is described for solving the reserve constrained economic dispatch problem when losses are considered.

Step 1: Initialization

Step 1.1: Initialization of problem: choose number of generator units, power demand, specify maximum and minimum capacity constraints of all generators, system spinning reserve requirement, cost coefficients of generator units, prohibited operating zones. B-coefficients for loss calculation, down and up ramp rates limits.

Step 1.2: Initialization algorithm parameters: choose population size *P*, number of memeplexes *m*, number of frogs in each memeplex *n* such that, *m x n=P*, Crossover Probability *CR*, Scaling Factor *F* and number of memetic evolutions *IE*, and set the maximum number of shuffled iterations *SI*.

Step 2: Initialize randomly the individual of the population according to the limits of each generating unit considering the ramp rate limits.If losses are absent go to step 4.

Step 3: Evaluate the system transmission loss using (3)

Step 4: Adjust the generations of units according to the following procedure for the power balance constraint satisfaction.

Procedure for Power balance satisfaction with power loss

```
If sum_power>Power_D+PLoss
    Error=Power_D+PLoss-sum_power
   /*generate integer z randomly in between [1,N] i.e.,z=ceil(1+(N-1)*rand()) */
    P(z)=P(z)+Error
    If P(z)>Pmax(z)
      Diff=P(z)-Pmax(z)
      P(z)=Pmax(z)
      For i =1 To Max
          If i~=z
              P(i)=P(i)+P(i)*diff/N
          End if
      End for
    End if
   For i =1 To Max
     If P(i)>Pmax(i)
       P(i)=Pmax(i)
    End if
  End for
 P(z)=Power_D+PLoss-sum(P(i, but i~=z))
 Else If sum_power<Power_D+PLoss
              Error= sum_power- Power_D+PLoss
/*generate integer z randomly in between [1,N] i.e.,z=ceil(1+(N-1)*rand()) */
      P(z)=P(z)-Error
       If  P(z)<Pmin(z)
         Diff= Pmin(z)-P(z)
         P(z)=Pmin(z)
        For i =1 To Max
            If i~=z
            P(i)=P(i)-P(i)*diff/N
            End if
        End for
      End if
 For i =1 To Max
     If P(i)<Pmin(i)
       P(i)=Pmin(i)
    End if
  End for
 End if
```

Step 5: Evaluate the fitness for each particle according to the objective function, including penalty functions as given in (10). The fitness function includes the total generation cost F_T and the penalty functions.

Step 6: Sort the population in descending order of their fitness. Assign the first population (frog) as global frog as X_g. Partition the memeplexes into *m* such that each memeplex will have *n* frogs each.
Step 7: Set *im*=0 (memeplex counter)
Step 8: Increment memeplex counter i.e., *im*=*im*+1;
Step 9: Set *ie*=0 (internal evolution counter)
Step 10: Increment internal evolution counter i.e., *ie*=*ie*+1;
Step 11: Set *in*=0 (frogs counter in a memeplex)
Step 12: Increment frog count i.e., *in*=*in*+1;
Step 13: Frog undergo DE mutation according to the equation (11), and crossover operations.
Step 14: Evaluate the system transmission loss if any, and adjust the power generations and calculate the augmented fuel cost using (10) and perform selection operation between old frog and newly generated one and select the new frog based on their fitness values.
Step 15: Check number of frogs in a memeplex,i.e., if $in \le n$ go to step 12
Step 16: Check number of internal evolution, i.e., if $ie \le IE$ go to step 10
Step 17: Check number memeplexes, i.e., if $im \le m$ go to step 8. Otherwise go to shuffling operation to form new memeplex sets
Step 18: Combine the memeplexes in to a single population
Step 19: Go to step 6 for the next iteration. This loop can be terminated after a predefined number of iterations.

IV. NUMERICAL EXAMPLE AND RESULTS

This section presents the computation results on 13-unit test system to evaluate the performance of the proposed SDE algorithm. A PED problem considering 13-unit power system from the literature has been investigated. In order to simulate the valve point effects of the generating units, a recurring sinusoid component is added with the objective function of fuel cost. However, many practical constraints of generators, such as ramp rate limits, prohibited operating zones, spinning reserve and power transmission loss are also considered in the optimization process. To verify the performance of the proposed algorithm, 13-unit system was repeatedly tested a hundred times by the SDE method. The results of fuel costs and average CPU times are used to compare the performance of the proposed SDE method with power those obtained in recent studies presented in the literature. The proposed algorithms were implemented using MATLAB 7.7 running on 'I3' Processor, 2.26 GHz, 3GB RAM PC.

Table 2
Optimal parameters setting of SDE methods for 13-unit systems

Parameter	Numerical value
P	100
m	10
n	10
F	0.2
CR	0.2
IE	5
SI	150

The population size (*P*) is 100 and total number of iterations is 150. The scaling factor and cross over parameters are fixed at the above values until the end of the total number of iterations. The 'DE/memeplexbest/2' mutation operator is used in the SDE. The number of memeplexes is 10 and the number of frogs in each memplex is 10. These settings of parameters for the SDE method are given in the Table 2.

The fuel cost function is solved for the 13-unit power systems by the proposed SDE algorithm and the data of the test system is obtained from [1], which includes thirteen generating units cost function and loss coefficients B matrix, with modification in the fuel cost functions to incorporate the spinning reserve, valve point loadings, prohibited zones and ramp rate limits. The total load demand of the system is 2520 MW and system provides a required spinning reserve of 180 MW at least. The input data including prohibited zones and ramp rate limits of the thirteen units are listed in the Appendix-A along with the fuel cost coefficients of the units. To verify the performance of the proposed SDE method, the results were compared with those methods reported in the literature which were applied to solve this system.

Fig. 1 displays the computed fuel cost of the 150 iteration. As shown in Fig. 1, the SDE algorithm has the most stable and minimum fuel cost. Thus, the SDE algorithm is more reliable to find out the global minimum fuel cost in this 13-unit system. The computational results of the SDE algorithm which satisfy the system constraints are listed in Table 3 and Table 4. From the computation results shown in Tables 3 and Table 4, it can be seen that the proposed algorithm has the potential to find the global solution. Among these approaches, the SDE algorithm results in the minimum fuel cost.

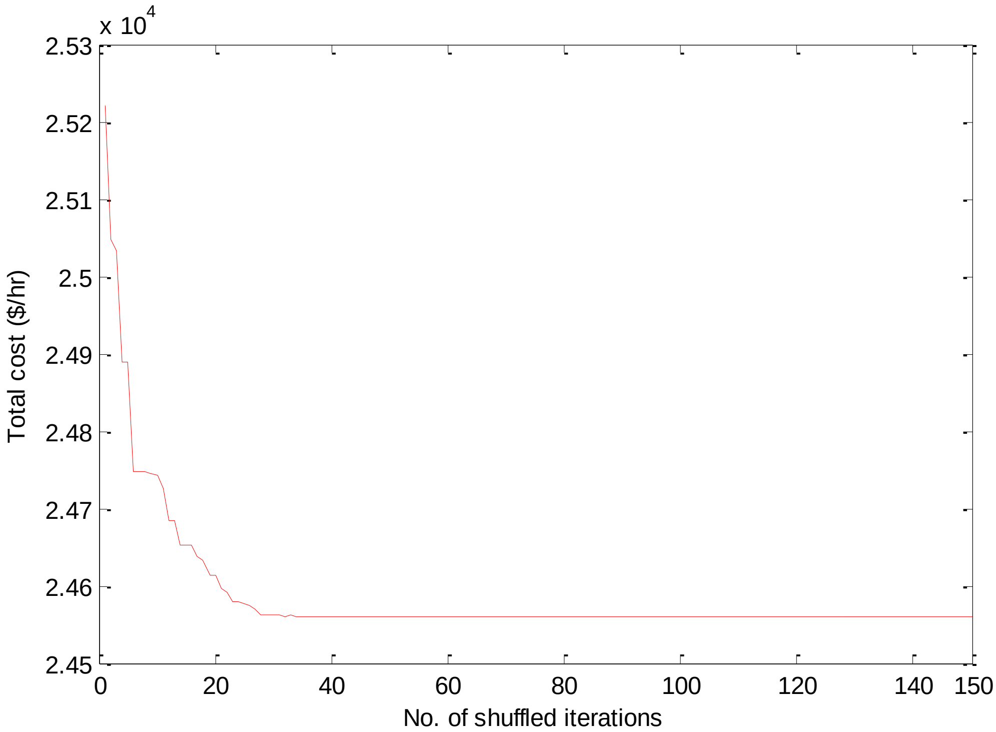

Figure 1: Convergence characteristic of 13-unit system for P_D= 2520 MW

Table 3
Results of different methods for 13-unit system considering all constraints

Unit	SDE	ICA-PSO [28-29]	STHDE [5]	HDE [5]	DE [5]	GA [5]
G1	628.3185	628.32	628.3185	628.3290	628.0117	628.4311
G2	299.1995	299.19	299.2092	299.3286	300.2498	305.0000
G3	299.1997	294.51	299.2018	304.5139	348.2995	302.6497
G4	159.7331	159.73	159.7416	159.7930	159.0591	158.9094
G5	159.7332	159.73	159.7433	159.8114	159.7318	160.4743
G6	159.7332	159.73	159.7335	159.8572	159.7324	159.7312
G7	159.7331	159.73	159.7384	159.9505	159.7330	160.1004
G8	159.7331	159.73	159.7331	109.8658	147.6877	159.6400
G9	159.7331	159.73	159.7338	159.7405	160.7340	109.6715
G10	114.7998	114.80	114.8027	114.8171	77.2938	114.5156
G11	114.7999	116.45	116.7061	115.7702	115.6040	116.2229
G12	57.1789	55.00	55.2551	94.9711	55.0112	92.0872
G13	92.4001	92.40	92.41379	92.40933	91.19282	92.4327
Total power output (MW)	2564.2953	2559.05	2564.33	2559.16	2562.34	2559.87
Minimum cost ($/hr)	44.2953	39.05	44.3314	39.15823	42.3412	39.8664
Spinning reserve (MW/hr)	189.4223	--	186.5761	190.8761	198.3218	198.3218
Minimum cost ($/hr)	**24558.7649**	24549.86*	24560.08	24591.76	24819.32	24632.42
Mean cost ($/hr)	24602.1578	-	24706.63	24739.53	25217.64	24874.93
Maximum cost ($/hr)	24654.3128	-	24872.44	25074.902	25656.40	25188.59
CPU time/iter (sec)	0.092	-	2.97826	3.57327	2.58151	2.25174

* Power balance violation and not considered as feasible solution

Table 4
Comparison of results for 13-unit system

Method	Total power output (MW)	Power loss (MW)	Total spinning reserve (MW)	Minimum cost ($/hr)
SDE	2564.30	44.2953	189.4223	**24558.77**
GA	2559.87	39.8664	198.3218	24632.42
DE	2562.34	42.3412	198.3218	24819.32
HDE	2559.16	39.15823	190.8761	24591.76
STHDE	2564.33	44.3314	186.5761	24560.08
ICA-PSO*	---	---	---	24549.86

* Power balance violation and not considered as feasible solution

V. Conclusions

In this paper, it has been suggested that employing the SDE algorithm to solve the non-smooth/non-convex ED problems considering spinning reserve constraint, and other constraints such as prohibited zones, ramp rate limits, valve point loadings gives best solutions. The results obtained proposed SDE optimization algorithm were compared with the results obtained by those methods reported in the literature. 13-unit test system has been employed to illustrate the application of the proposed method. Computational results show that the proposed SDE algorithm is superior to the other algorithms in terms of computed minimum fuel cost and computational complexity.

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