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Shuffled Differential Evolution for Economic Load Dispatch Problem

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Abstract: Electrical power industry restricting has created highly vibrant and competitive market that altered many aspects of the power industry. In this changed scenario, scarcity of energy resources, increasing power generation cost, environment concern, ever growing demand of electrical energy necessitate optimal economic dispatch. Practical economic dispatch (ED) problems have nonlinear, non-convex type objective function with intense equality and inequality constraints. The conventional optimization methods are not able to solve such problems as due to local optimum solution convergence. This work proposes a novel metaheuristic optimization methodology aimed at solving economic dispatch problem considering valve point loading effects. The differential evolution (DE) may occasionally stop proceeding toward the global optimum even though the population has not converged to a local optimum. 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. Shuffled frog leaping algorithm (SFLA) is a newly developed mimetic metaheuristic algorithm for combinatorial optimization, which has simple concept, few parameters, high performance, and easy programming. SFLA and its variants have been successfully applied to various fields of power system optimization. The proposed approach is based on a hybrid shuffled differential evolution (SDE) algorithm which combines the benefits of SFLA and DE. The SDE algorithm integrates a novel differential mutation operator specifically designed to effectively address the problem under study. In order to validate the proposed methodology, detailed simulation results obtained on three standard test systems having 3, 13, and 40-units are presented and discussed. A comparative analysis with other settled nature-inspired solution algorithms demonstrates the superior performance of the proposed methodology in terms of both solution accuracy and convergence performances.

Keywords: Particle Swarm Optimization, Load Dispatch, Shuffled Frog Leaping Algorithm.

I INTRODUCTION

A certain load demand existing at any instant of time in a power system may be supplied in an infinite number of configurations. In the load flow problem if the specified variable P, V at generator buses are allowed to vary in a region constrained by practical consideration (upper and lower limits of active and reactive power, bus voltage limit), then for a certain P-Q values of load buses there results an infinite number of load flow solutions each pertaining to one set of values of specified P, V (control variables). The best choice in some sense of the values of control variables leads to the best load flow solution.
Operating economy is naturally predominant in determining the best choice; though there are several others equally important factors (which we shall not consider here for simplicity) should be given consideration. Economic operation of power systems calls for the selection of the best operating configuration that gives maximum operating economy or minimum operating cost. The total operating cost includes fuel, lab our, and maintenance costs, but for simplicity we shall assume that the only cost that we need to consider are fuel costs for power production as these makes the major portion of the total operating (variable) cost and are directly related to the value of power output. The reactive power generation has no appreciable influence on the fuel consumption and the fuel cost is critically dependent on real power generation. Fuel cost characteristics (fuel cost vs. net active power output) of different units may be different giving different economic efficiency. So the problem of selecting the optimum operating configuration reduces to the problem of finding an optimal combination of generating units to run and to allocate these real power generations.

Load variations consequently necessitate the calculation of new optimum configuration. However, the starting up procedure of a generating unit (particularly steam unit) must begin long (some hrs) before it should be connected to the system. Therefore, the combination of the units that should be run at a particular time must be selected several hrs in advance so that they may be started up and synchronized prior to loading, whereas their optimum generation setting can be calculated almost instantaneously when required during the actual time of running. A subdivision within the overall problem is therefore apparent. The problem of selection of combination of units must be solved well before its actual implementation and thus it is a problem of operation planning generally known as unit ordering or unit commitment. The problem related to the allocation or change in allocation of the power outputs of the generators connected to the system at a particular time in a manner which minimize the operating (fuel) cost of the system is a real time problem

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known as Economic Dispatch. This thesis is concerned with the economic dispatch problem of all thermal systems only. It is to be note that all the generating units in a system do not participated in the economic dispatch. Nuclear units and very large steam units are run at constant MW setting as it is desirable (due to some technical reasons) to maintain the output of such units at as constant a level as possible. Fuel costs in base-load units then appear as a fixed cost and do not appear in the economic dispatch problem. We consider the minimization of those costs that, by proper strategy, we can control, i.e. the fuel costs in the controllable units.
The problem of economic operation of a power system or optimal power flow can be state as: Allocating the load (MW) among the various units of generating stations and among the various generating stations in such ways that, the overall cost of generation for the given load demand is minimum.
This is an optimization problem, the objective of which is to minimize the power generation cost function subject to the satisfaction of a given set of linear and non-linear equality and inequality constraints. The problem is analyzed, solved and then implemented under online condition of the power system. The input data for the problem comes from conventional power flow study. For a given load demand, power flow study can be used to calculate of active and reactive power generations, line flows and losses. The study also furnishes some control parameters such as the magnitude of voltage and voltage phase differences. The economic scheduling problem can be understood as an outcome of multiple power flow studies, where a particular power flow studies result is considered more appropriate in terms of cost of generation. The solution to this problem cannot be optimal unless otherwise all the constraints of the system are satisfied. We discuss the economic scheduling problem in the following sections, but first we consider the constraints that need to be addressed.

II LITERATURE SURVEY

Economic dispatch (ED) is one of the most fundamental and most heavily used tools in power engineering studies. It allows power systems analysts to schedule the committed generating unit outputs so as to meet the required load demand at minimum operating cost while satisfying all unit and system equality and inequality constraints [1]. The overall problem can be formalized as a nonlinear constrained optimization problem that can be solved by traditional nonlinear programming methods as far as k-iteration and gradient methods are concerned [2]. These techniques approximate the generator fuel cost functions by a quadratic polynomial and try to solve the constrained optimization problem by using an iterative search algorithm.
All these could result in non-optimal solutions and time consuming computations. In order to try and overcome some of aforesaid limitations more sophisticated solution algorithms have been proposed in literature. In particular paper [5] proposes the application of a dynamic programming based algorithm. Although this algorithm has no restrictions on the shape of the cost curve, it performances tends to deteriorate as the number of generators increases [5]. In particular the ED problem solution considering valve point effects have been addressed by: evolutionary programming (EP) [6]; improved fast EP (IFEP) [7]; genetic algorithm (GA) [3]; particle swarm optimization (PSO) combined with the SQP method (PSO–SQP) [8]; Differential evolution (DE) is an evolutionary computation method for optimizing nonlinear and non-differentiable continuous space functions developed by Stern and Price [24]. DE may occasionally stop proceeding toward the global optimum even though the population has not converged to a local optimum.
Shuffled frog leaping algorithm (SFLA) is a newly developed mimetic metaheuristic algorithm for combinatorial optimization, which has simple concept, few parameters, high performance, and easy programming [25]. Recently, SFLA and its variants have been successfully applied to various fields of power system optimization [26–29]. Specifically, an efficient multi-objective modified shuffled frog leaping algorithm (MMSFLA) used to solve distribution feeder reconfiguration (DFR) problem in [26]. In [27], an efficient tribe-modified shuffled frog leaping algorithm (T-MSFLA) presented to solve multi-objective DFR problem. A novel hybrid algorithm (SFLA–SA) [28] proposed based on SFLA and simulated annealing (SA) for solving the optimal power flow (OPF) problem with non-smooth and non convex generator fuel cost characteristics.

III SHUFFLED DIFFERENTIAL EVOLUTION FOR ECONOMIC LOAD DISPATCH PROBLEM

In this chapter, we review the shuffled differential evolution (SDE) algorithm that was used for searching the optimum solution of ELD problems. SDE is a frog population-based stochastic search technique that works in the general framework of DE. The design principles of SDE are simplicity, efficiency and use of real coding. It starts to explore the search space by randomly choosing the initial candidate solutions within the boundary. Then the algorithm tries to locate the global optimum solution for the problem by iterated refining of the population through reproduction and selection. In addition to the optimization technique, there is a need to develop algorithm for handling constrains. All the constrained handling techniques that came out over the last few years into four categories: (1) methods based on preserving feasibility of solution often using some specialized operators to transform infeasible solutions into feasible ones, (2) methods based on penalty functions where fitness of infeasible individuals are penalized in different ways, (3)

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methods which make a clear separation between feasible and infeasible solutions and often prefers a feasible one with lower objective value over an infeasible one with higher objective value and (4) hybrid methods that combines evolutionary techniques with deterministic procedures. The primary objective of ELD problem is to determine the most economic loading of the generating units such that the load demand in the power system can be met [3]. Additionally, the ELD planning must be performed satisfying different equality and inequality constraints. In general, the problem is formulated as follows. Consider a power system having N generating units, each loaded to P_iMW. The generating units should be loaded in such a way that minimizes the total fuel cost F_T while satisfying the power balance and other constraints. Therefore, the classic ELD problem can be formulated as an optimization process with the objective:

$$minimum\ F_T = min \sum_{i=1}^{N} F_i(P_{G,i}) \quad \textbf{(4.1)}$$

where the fuel input–power output cost function of isith unit is represented by the function F_i. The most simplified fuel cost function $F_i(P_i)$ for generator i loaded with P_iMW is approximated by a quadratic function as follows:

$$F_i(P_{G,i}) = a_i P_{G,i}^2 + b_i P_{G,i} + c_i \quad \textbf{(4.2)}$$

Where a_i, $b_i$and c_i are the fuel cost coefficients of the ith generatic unit. i = 1, 2, ……N

In reality, the generating units with multi-valve steam turbine have very different input–output curve compared with the smooth cost function. Therefore, the inclusion of the valve-point loading effects makes the representation of the incremental fuel cost function of the generating units more practical. The incremental fuel cost function of a generating unit with valve-point loadings is represented as follows:

$$F_i(P_{G,i}) = a_i P_{G,i}^2 + b_i P_{G,i} + c_i + |e_i \times \sin(f_i \times (P_{G,i\,min} - P_{G,i}))| \quad \textbf{(4.3)}$$

Where e_i and f_i are the coefficients of generator i reflecting the valve-point effects.

Constraint handling technique

Equality constraints handling (i.e., power balance) represent one of the most complex issues to address in ED analysis. In this connection the application of penalty functions requires large penalty factors in order to make the ED problem feasible. These large values could distort the solution space leading the solution algorithm to diverge or to converge to a weak local optimum. In order to try and overcome this limitation in this chapter a novel technique for equality constraint handling is proposed.

The constraint handling procedure is based on the following steps:

Step1: Determine the sum of total generation i.e.,$\sum_{i=1}^{N} P_{G,i}$

Step2: Calculate power mismatch i.e., Error=$\sum_{i=1}^{N} P_{G,i} - P_D$

Step 3: If Error = 0 go to step 14

Step 4: Generate a random integer z between 1 and N

Step 5: Adjust the difference of power to P_z, i.e.,$P_z = P_z$ - Error

Step6: If P_z is within the limits go to step 14. If $P_z > P_{z,max}$go to step 10

Step7: Diff =$P_{z,min}$- P_z and

Step8: Adjust the power outputs of the remaining generators i.e., except P_z, according to the following equation:

$P_i = P_i * (1 - Diff/N);i \neq z$, and for i = 1, 2, . . . ,N

Step 9: Check for power limit after the adjustments

i.e., If $P_i < P_{i,min};i \neq z$, and for i = 1, 2,. . . , N

$P_i = P_{i,min}$go to step 14

Step 10: Diff = P_z- $P_{z,max}$

Step 11: $P_z = P_{z,max}$

Step12: Adjust the power outputs of the remaining generators, except P_z, according to the following equation:

$P_i = P_i * (1 + Diff/N);i \neq z$, and for i = 1, 2, . . . , N

Step 13: Check for power limit after the adjustments:

i.e., If $P_i > P_{i,max}$for $i \neq z$, and for i = 1, 2, . . . , N

$P_i = P_{i,max}$

Step 14: Stop constraint handling

The application of the proposed constraint handling procedure is expected to overcome the main limitations of the standard penalty function method avoiding the distortion of the solution space induced by large penalty factors. Besides it allows the solution algorithm to decrease the pressure of constraint violation error on the fitness function. This improves the solution domain exploration and, consequently, the quality of the solution.

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The application of the SDE algorithm for ED analysis

In this chapter, the proposed SDE algorithm is applied for solving the non convex economic dispatch problem formalized in Chapter 3. The main steps characterizing the search procedure are here analyzed:

Step 1: Specify the generator cost coefficients and valve-point coefficients, choose number of generator units (N), specify maximum and minimum capacity constraints of all generators and load demand P_D. Initialize SDE parameters.

Step 2: An initial population of frogs (X) is created randomly foran N-dimensional problem (number of generating units).

$$X = \begin{bmatrix} X_1 \\ X_2 \\ \vdots \\ \vdots \\ X_p \end{bmatrix} = \begin{bmatrix} x_{1,1} x_{1,2} & \cdots & \cdots & x_{1,N} \\ x_{2,1} x_{2,2} & \cdots & \cdots & x_{2,N} \\ \vdots \quad \vdots & & & \vdots \\ \vdots \quad \vdots & & & \vdots \\ x_{p,1} x_{p,2} & \cdots & \cdots & x_{p,N} \end{bmatrix} \tag{4.4}$$

A frog i is represented by N decision variables, such as $X_i = (x_{i,1}, x_{i,2}, x_{i,3}, \ldots., x_{i,N})$. Since the decision variablesfor the ED problems are real power generations, theyare used to represent each element of a given population of virtual frogs. Each frog of the population matrix should satisfy equality constraint. The element of the virtual frog's matrix is initialized randomly within the effective real power operating limits as

$$x_{j,i} = p_{i,min} + rand().(p_{i,max} - p_{i,min}) \tag{4.5}$$

where$x_{j,i}$ is the power output i.e., j^{th} population of i^{th} unit and rand() is a random number between 0 and 1. Each individual must be a feasible candidate solution that satisfies the inequality constraint. Each frog undergoes equality constraint handling procedure before evolution.

Step 3: Even after the completion of constraint handling procedure, if there is any power balance violations such solutions are eliminated by adding a penalty term in their fitness function [36]. Calculate the fitness function (JF)using (4.6).

$$\mathrm{JF} = \frac{1}{\mathrm{FT} + \mu\left|\sum_{i=1}^{n} P_i - P_D\right|} \tag{4.6}$$

whereμ is penalty factor. In this work μ is taken as 1.

Step 4: Set iis = 0 (shuffled iteration counter)

Step 5: Increment the shuffled iteration counter i.e., iis=iis+1;

Step 6: Sort the population in descending order of their fitness. Assign the first population (frog) as global frog, Xg. Partition the entire population into m meme lexes such that each containing n frogs.

Step 7: Apply the memetic evolution step, the group of frogs ineach memeplex acts and evolves as an independent culture;

Step 8: After IE number of internal evolution within eachmemeplex the population is shuffled.

Step 9: If the maximum number of shuffled iterations is notreached, i.e., if iis≤SI, go to the steps 5.

Step 10: Print best solution and stop.

IV. CASE STUDIES AND DISCUSSION

The proposed algorithm is implemented using MATLAB 8.1 running on 'i5' Processor, 2.2 GHz, and 4 GB RAM personal computer. In order to demonstrate the performance of the proposed SDE method, it was tested on three benchmark power system case studies. In this chapter, ED problem is solved with valve point loading effects considered 3, 13, and 40-unit case study systems with minimum active power in MW (P_{min}), maximum active power in MW(P_{max}), a, b, & c cost coefficients of generator and e & f cost coefficients of generator reflecting valve-point loading effects in Table A1, A2 and A3 respectively. The results are compared with well settled nature-inspired and bio-inspired optimization algorithms.

Case studies and Analysis:

4.1 Three unit case study system

A system of three thermal units with the effects of valve-point loading was studied in this case study and the respective data is given in the Table A1 with all required values. The expected load demand to be met by all the three generating units is 850 MW. The system data can be found from [7]. The convergence profile of the cost function is depicted in Fig. 4.1. The dispatch results using the proposed method and other algorithms are given in Table 4.1. The global optimal solution for this case study system is reported in [12] as 8234.07 $/h. From Table 4.1, it is clear that the proposed method SDE reported the global optimal solution.

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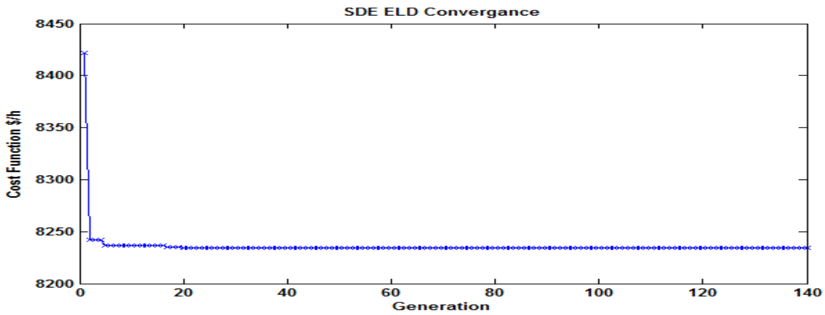

Fig. 4.1 Convergence profile of the total cost for 3 generating units

Table 4.1 Comparisons of simulation results of different methods for 3-unit case study system

Unit	GA [3]	MPSO [12]	SDE
1	300.00	300.27	300.2669
2	400.00	400.00	400.0000
3	150.00	149.74	149.7331
Total power in MW	850.00	850.00	850.0000
Total cost in $/h	8234.60	8234.07	8234.0717

In the Table 4.1, SDE method is also compared with the GA [3] and MPSO [12] methods. The minimum cost for GA [3] and MPSO [12] is 8234.60 $/h and 8234.07 $/h respectively Fig. 4.2 shows the distribution of total costs of the SDE algorithm for a load demand of 850 MW for 100 different trials for 3-unit case study and observed that the maximum, minimum and average values are 8250.2047 $/h, 8234.0717 $/h and 8240.9518 $/h respectively. The mean values also highlighted with red line in the fig. 4.2.

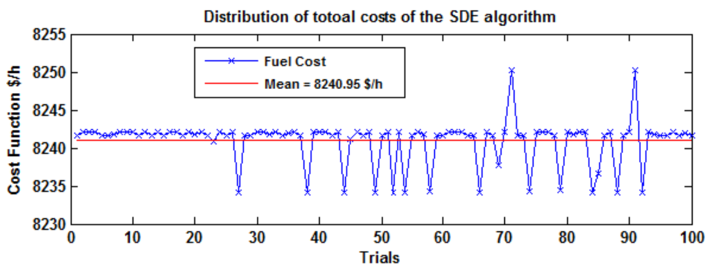

Fig. 4.2 Distribution of total costs of the SDE algorithm for a load demand of 850 MW for 100 different trials for 3-unit case study

4.2 Thirteen unit case study system

The proposed hybrid algorithm is applied on 13-unit system with the effects of valve-point loading.

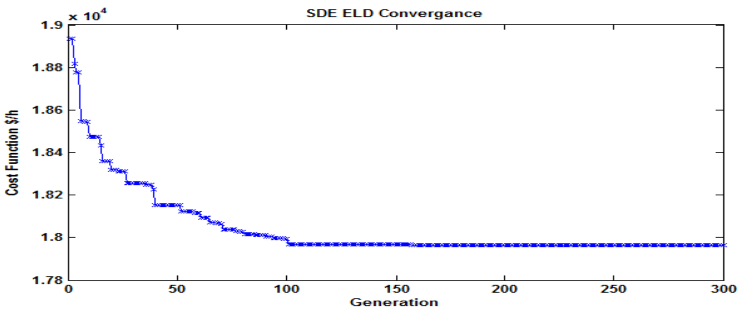

Fig. 4.3 Convergence profile of the total cost for 13 generating units with PD = 1800 MW

The problem is solved for two different power demands in order to show the effectiveness of the proposed method in producing quality solutions. In the first case, the expected load demand to be met by all the thirteen generating units is 1800 MW. The load demand is set at 2520 MW in second case. The data of the test system have been obtained by [7].

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Table 4.2 Comparisons of simulation results of different methods for 13-unit case study system with P_D = 1800 MW

Unit	IGA_MU [41]	HQPSO [42]	SDE
1	628.3151	628.3180	628.3185
2	148.1027	149.1094	222.7493
3	224.2713	223.3236	149.5995
4	109.8617	109.8650	60.0000
5	109.8637	109.8618	109.8665
6	109.8643	109.8656	109.8665
7	109.8550	109.7912	109.8665
8	109.8662	60.0000	109.8665
9	60.0000	109.8664	109.8665
10	40.0000	40.0000	40.0000
11	40.0000	40.0000	40.0000
12	55.0000	55.0000	55.0000
13	55.0000	55.0000	55.0000
Total power in MW	1800.0000	1800.0000	1800.0000
Total cost in $/h	17963.9848	17963.9571	17963.8293

Table 5.2 shows the best dispatch solutions obtained by the proposed method for the load demand of 1800 MW. The convergence profile for SDE method is presented in Fig. 4.3. The results obtained by the proposed methods are compared with those available in the literature as given in Table 4.2. The minimum cost obtained by SDE method is 17963.8293 $/h, which is the best cost found so far and also compared the SDE method with the IGA_MU [41] and HQPSO [42] methods. The minimum cost for IGA_MU [41] and HQPSO [42] is 17963.9848 $/h and 17963.9571 $/h respectively. The results demonstrate that the proposed algorithm outperforms the other methods in terms of better optimal solution. Fig. 4.4 shows the variations of the fuel cost obtained by SDE for 100 different runs and convergence results for the algorithms are presented in Table 4.3 for 1800MW load.

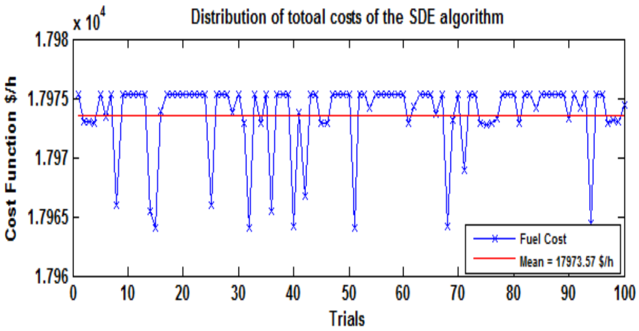

Fig. 4.4Distribution of total costs of the SDE algorithm for a load demand of 1800 MW for 100 different trials for 13-unit case study

Fig shows the variations of the fuel cost obtained by SDE for 100 different runs and convergence results for the algorithms are presented in Table 4.3 for 1800MW load.

Table 4.3 Convergence results (100 trial runs) for 13-unit test system with P_D = 1800 MW

Method	Minimum cost ($/h)	Average cost ($/h)	Maximum cost ($/h)
IGA_MU [41]	17963.9848	NA	NA
HQPSO [42]	17963.9571	18273.8610	18633.0435
SDE	17963.8293	17972.8774	17975.3434

Table 4.3 shows the convergence results for 100 trials for 13-unit test system with load 1800 MW and compared the minimum, average and maximum cost for IGA_MU [41] and HQPSO [42] methods. It has been observed that minimum, average and maximum costs for SDE proposed method is 17963.8293 $/h, 17972.8774 $/h and 17975.3434 $/h respectively and also observed that the proposed method minimum, average and maximum cost values are low compared with the IGA_MU [41] and HQPSO [42] methods.

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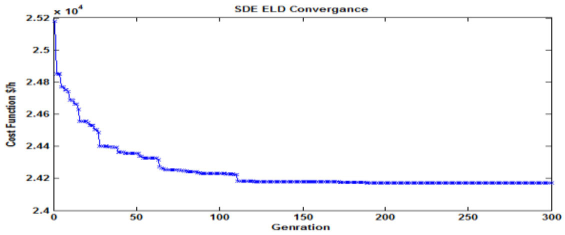

Fig. 4.5 Convergence profile of the total cost for 13 generating units with PD = 2520 MW

Table 5.4 shows the best dispatch solutions obtained by the proposed method for the load demand of 2520 MW. The convergence profile for SDE method is presented in Fig. 4.5. The results obtained by the proposed methods are compared with those available in the literature as given in Table 4.4. Though the obtained best solution is not guaranteed to be the global solution, the SDE has shown the superiority to the existing methods. The minimum cost obtained by SDE method is 24169.9177$/h, which is the best cost found so far and also compared the SDE method with the GA_MU [48] and FAPSO-NM [20] methods. The minimum cost for GA_MU [48] and FAPSO-NM [20] is 24170.7550 $/h and 24169.92 $/h respectively.

Table 4.4 Comparisons of simulation results of different methods for 13-unit case study system with P_D = 2520 MW

Unit	GA_MU [48]	FAPSO-NM [20]	SDE
1	628.3179	628.32	628.3185
2	299.1198	299.20	299.1993
3	299.1746	299.98	299.1993
4	159.7269	159.73	159.7331
5	159.7269	159.73	159.7331
6	159.7269	159.73	159.7331
7	159.7302	159.73	159.7331
8	159.7320	159.73	159.7331
9	159.7287	159.73	159.7331
10	159.7073	77.40	77.3999
11	73.2978	77.40	77.3999
12	77.2327	87.69	92.3999
13	92.2598	92.40	87.6845
Total power in MW	2520.0000	2520.0000	2520.0000
Total cost in $/h	24170.7550	24169.92	24169.9177

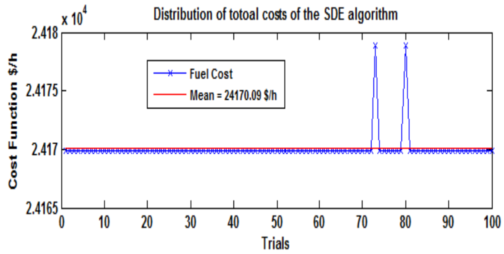

Fig. 4.6 Distribution of total costs of the SDE algorithm for a load demand of 2520 MW for 100 different trials for 13-unit case study

The results demonstrate that the proposed algorithm outperforms the other methods in terms of better optimal solution. Fig. 4.6 shows the variations of the fuel cost obtained by SDE for 100 different runs and convergence results for the algorithms are presented in Table 4.3 for 2520 MW load.

Table 4.5 Convergence results (100 trial runs) for 13-unit test system with P_D = 2520 MW

Method	Minimum cost ($/h)	Average cost ($/h)	Maximum cost ($/h)
GA_MU [48]	24170.7550	24429.1202	24759.3120
FAPSO-NM [20]	24169.9200	24170.0017	24170.4402
SDE	24169.9176	24170.0960	24178.8346

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Table 4.3 shows the convergence results for 100 trials for 13-unit test system with load 1800 MW and compared the minimum, average and maximum cost for GA_MU [48] and FAPSO-NM [20] methods. It has been observed that minimum, average and maximum costs for SDE proposed method is 17963.8293 $/h, 17972.8774 $/h and 17975.3434 $/h respectively.

4.2.3 Forty unit case study system

The ED problem has been solved for a 40 thermal unit's power system considering the effects of valve-point loading effects. The load demand is 10500 MW. The system data can be found in [7] and given in Table A3.

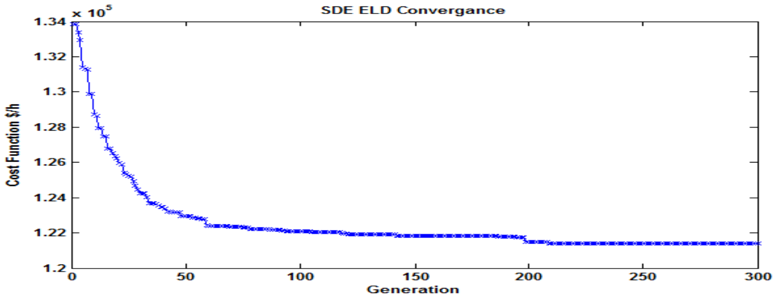

Fig. 4.7: Convergence profile of the total cost for 40 generating units with PD = 10500 MW

The Fig. 4.7 shows the convergence profile for the total cost for 40 generating units with load of 10500 MW. The results obtained by applying the SDE solution algorithm are summarized in Table 4.6. Analyzing the data, it can be observed as the SDE method succeeds in finding a satisfactory solution. The minimum cost obtained by SDE method is 121412.5355 $/h, which is the best cost found so far. This statement is also confirmed by analyzing Table 4.7 which summarizes the minimum, average, and maximum cost obtained by other settled algorithms. The analysis of these comparative results demonstrates that the proposed approach shows superior performance compared to other settled methods reported in the literature. Fig. 4.8 shows the variations of the fuel cost obtained by SDE for 50 different runs for forty unit system.

Table 4.6 Simulation results for 40-unit case study system with P_D = 10500 MW

Unit	SDE	Unit	SDE
1	110.7889	21	523.2794
2	110.7998	22	523.2794
3	97.3999	23	523.2794
4	279.7331	24	523.2794
5	87.7999	25	523.2794
6	140.0000	26	523.2794
7	259.5996	27	10.0000
8	284.5996	28	10.0000
9	284.5996	29	10.0000
10	130.0000	30	87.7999
11	94.0000	31	190.0000
12	94.0000	32	190.0000
13	214.7598	33	190.0000
14	394.2794	34	164.7998
15	394.2794	35	200.0000
16	394.2794	36	194.3978
17	489.2794	37	110.0000
18	489.2794	38	110.0000
19	511.2794	39	110.0000
20	511.2794	40	511.2794
Total power in MW			10500.0000
Total cost in $/h			121412.5355

Table 4.3 shows the convergence results for 100 trials for 13-unit test system with load 1800 MW and compared the minimum, average and maximum cost for BBO [16] and ACO [50] methods. It has been observed that minimum, average, maximum costs SDE proposed method is 121412.5355$/h, 121474.0032$/h and 121521.0211$/h respectively

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Table 4.7 Convergence results (100 trial runs) for 40-unit test system with P_D = 10500 MW

Method	Minimum cost ($/h)	Average cost ($/h)	Maximum cost ($/h)
BBO [16]	121426.9530	121508.0325	121688.6634
ACO [50]	121811.3700	121930.5800	122048.0660
SDE	121412.5355	121474.0032	121521.0211

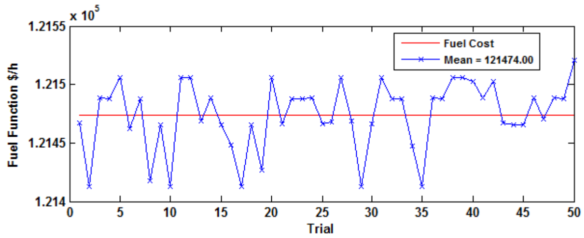

Fig. 4.8: Distribution of total costs of the SDE algorithm for a load demand of 10500 MW for 100 different trials for 40-unit case study

4.3 Convergence characteristic and computational efficiency

The convergence profiles for SDE method for three unit system with 800 MD load, thirteen unit system with 1800 MW and 2520MW load and forty unit test system with 10500 MW are presented in fig. 4.1, fig. 4.3, fig. 4.5 and fig. 4.7 respectively. From the convergence profiles, it was clear that the minimum cost is obtained by SDE within 100iterationsfor three unit system and thirteen unit system and 50 iterations for forty unit system. Fig. 4.2, fig. 4.4, fig. 4.6 and fig. 4.8 shows the convergence profiles for the higher number of iterations for three unit system, thirteen unit system and forty unit system respectively.

Table 5.8CPU time comparison for 40-unit test system

Method	CPU time in sec
BBO [16]	42.98
ACO [50]	92.54
SDE	27.69

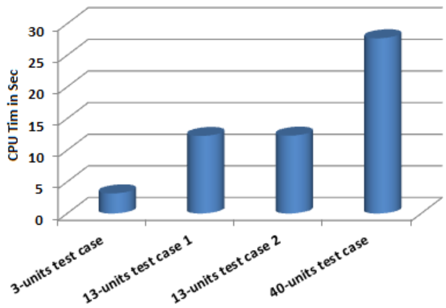

Fig.5.9: CPU times of SDE method for different systems

It is observed that from Table 4.8, the SDE method is computationally efficient than the mentioned methods. The Average CPU times of SDE method for different systems are shown in Fig. 4.9.

V CONCLUSIONS AND FUTURE SCOPE

Economic Load Dispatch is one of the fundamental issues in power system operation. The problem of economic load dispatch with equality and inequality constraints has been investigated in this thesis. A novel hybrid heuristic method has been considered with simple active power balance, generation unit limits and valve point loading and successfully applied for non convex economic dispatch problems solution. The proposed approach is based on a hybrid shuffled differential evolution (SDE) algorithm which combines the benefits of shuffled frog leaping algorithm and differential evolution. The SDE algorithm integrates a novel differential mutation operator specifically designed for effectively addressed the problem. In order to validate the proposed methodology, detailed simulation results obtained on three standard test systems having 3, 13, and 40-units have been presented and discussed. The simulation results showed as

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the proposed method succeeded in achieving the goal of reduction generation costs. Comparative analysis with other settled nature-inspired solution algorithms demonstrated the superior performance of the proposed methodology in terms of both solution accuracy and convergence performances. Also it has better results compared to the other existing optimization techniques in terms of generation cost and constraints satisfactions and computation time. Therefore, the proposed method can greatly enhance the searching ability; ensure quality of average solutions, and also efficiently manages the system constraints.

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