

Solving economic dispatch with valve point loading effects by using optimization techniques

G. Chandrakala¹, V. Ramakrishna² Jan Bhasha Shaik³

¹(Department of Electrical and Electronics Engineering, Audisankara Institute of Technology & Science, Andhra Pradesh, India)

²(Department of Electrical and Electronics Engineering, College, Sri Venkateswara University, Andhra Pradesh, India)

³(Department of Electrical and Electronics Engineering, Audisankara Institute of Technology & Science, Andhra Pradesh, India)

ABSTRACT : *The economic dispatch problem with valve point loading effects may cause a small change in the objective function formulation. Due to valve point loading effects mechanism, complexity will come into picture and some other additionalities will include. Hence, we use strong optimization techniques to determine the minimum fuel cost for generation. The proposed optimization technique is based on a hybrid shuffled differential evolution (SDE) algorithm which combines the benefits of shuffled frog leaping algorithm and differential evolution to give optimal solution. 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 two standard test systems 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 and performances.*

KEYWORDS: *Differential evolution, Nonconvex economic dispatch, Shuffled frog leaping algorithm, Valve point loading effects.*

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, labour, 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. Obviously power generation by hydro units is much cheaper and can give much better operating economy. But the operation of such plants are dependent on the availability of water which is however restricted and subject to seasonal variations. In those systems, where both thermal and hydro sources are available, economy can be achieved by properly mixing the two types of generations. 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. 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, its 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 [3]; particle swarm optimization (PSO) combined with the SQP method (PSO-SQP) [8]; improved coordinated aggregation-based PSO (ICA-PSO) [9]; quantum-inspired particle swarm optimization (QPSO) [10]; combining of chaotic differential evolution quadratic programming (DEC-SQP) [11]; firefly algorithm (FA) [12].

Differential evolution (DE) is an evolutionary computation method for optimizing non-linear and non-differentiable continuous space functions developed by Storn and Price [13]. 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 memetic metaheuristic algorithm for combinatorial optimization, which has simple concept, few parameters, high performance, and easy programming [14]. Recently, SFLA and its variants have been successfully applied to various fields of power system optimization[15-18].

The main benefits of SFLA is its fast convergence while its main drawbacks are mainly due to the insufficient learning mechanism for the swarm that could lead to noncomprehensive solution domain exploration. In order to overcome the intrinsic limitations of DE and SFLA, emphasizing at the same time their benefits, an innovative technique called shuffled differential evolution (SDE) characterized by a novel mutation operator has been designed. The main contributions of this paper are:

- (1) Presenting a novel mutation operator to enhance the search ability of the SDE. And the mutation operator is specific to this work and has been never presented in the previous search works in the area.
- (2) Applying the proposed methodology to two benchmark ED problems with valve point loading effects and the results are presented.
- (3) The best results obtained from the solution of the ED problem by adopting the SDE algorithm are compared to those published in the recent state-of-the art literatures.

II. OPTIMIZATION PROBLEM FORMATION FOR ECONOMIC LOAD DISPATCH

The input-output characteristic of the whole generating unit system can be obtained by combining directly the input-output characteristic of the boiler and the input-output characteristic of the turbine-generator unit. It is a smooth convex curve, which is shown in Fig. 1

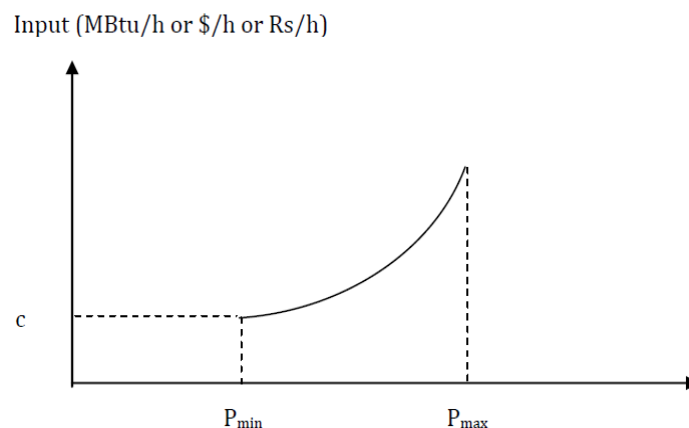


Fig.1 Input-output Characteristic of generating unit

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_i MW. 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:

$$\text{minimum } F_T = \min \sum_{i=1}^N F_i(P_{G,i}) \tag{1}$$

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

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

Where a_i , b_i and c_i are the fuel cost coefficients of the i^{th} generatic unit.
 $i = 1, 2, \dots, N$

2.1. Economic Dispatch problem considering valve-point loading effect

For more rational and precise modeling of fuel cost function, the above expression of cost function is to be modified suitably. The generating units with multi-valve steam turbines exhibit a greater variation in the fuel-cost functions [3]. The valve opening process of multi-valve steam turbines produces a ripple-like effect in the heat rate curve of the generators. These “valve-point effect” are illustrated in Fig.2.

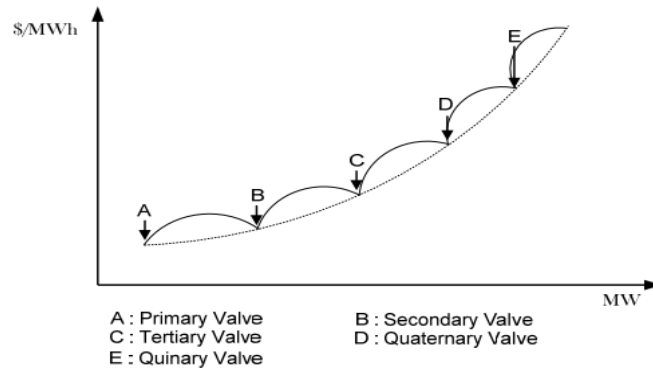


Fig. 2. Valve Point loading effect

The significance of this effect is that the actual cost curve function of a large steam plant is not continuous but more important it is non-linear. 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:

$$F_i(P_{G,i}) = a_i P_{G,i}^2 + b_i P_{G,i} + c_i + |e_i \times \sin(f_i \times (P_{G,i \text{ min}} - P_{G,i}))| \tag{3}$$

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

2.2 Constraints

2.2.1 Equality Constraints for Active Power Balance

The total power generated should be the same as the total load demand plus the total transmission losses. In this work, transmission power losses have not been considered and the active power balance can be expressed as:

$$\sum_{i=1}^N P_{G,i} = P_D \tag{4}$$

where P_D is the total power demand in MW.

2.2.2 Inequality Constraints for Generation Capacity

It is not always necessary that all the units of a plant are available to share a load. Some of the units may be taken off due to scheduled maintenance. Also it is not necessary that the less efficient units are switched off during off peak hours. There is a certain amount of shut down and startup costs associated with shutting down a unit during the off peak hours and servicing it back on-line during the peak hours. To complicate the problem further, it may take about eight hours or more to restore the boiler of a unit and synchronizing the unit with the bus. To meet the sudden change in the power demand, it may therefore be necessary to keep more units than it necessary to meet the load demand during that time. This safety margin in generation is called *spinning reserve*. The optimal load dispatch problem must then incorporate this startup and shut down cost for without endangering the system security.

The power generation limit of each unit is then given by the inequality constraints

$$P_{\min,i} \leq P_i \leq P_{\max,i} \quad i = 1, \dots, N \quad (5)$$

The maximum limit P_{\max} is the upper limit of power generation capacity of each unit. On the other hand, the lower limit P_{\min} pertains to the thermal consideration of operating a boiler in a thermal or nuclear generating station. An operational unit must produce a minimum amount of power such that the boiler thermal components are stabilized at the minimum design operating temperature.

III. SHUFFLED DIFFERENTIAL EVOLUTION OPTIMIZATION

In trying to address nonconvex ED problems the adoption of a hybrid solution technique based on a combination of differential evolution (DE) and shuffled frog leaping algorithm (SFLA) is proposed in this paper. In order to try and overcome the intrinsic limitations of DE and SFLA in solving nonconvex ED problems, an innovative technique called shuffled differential evolution (SDE) characterized by a novel mutation operator is proposed here. The proposed algorithm is based on the shuffling property of SFLA and DE algorithm. Similarly to other evolutionary algorithms, in SDE a population is initialized by randomly generating candidate solutions. The fitness of each candidate solution is then calculated and the population is sorted in descending order of their fitness. The fitness of each candidate solution is then calculated and the population is sorted in descending order of their fitness and partitioned into memplexes.

3.1. SDE parameters

The effective application of the SDE algorithm requires a proper setting of its control parameters. They include the population size (P), the number of memplexes (m), the number of frogs in a memplex (n), the maximum number of internal evolution or infection steps (IE) in a memplex between two successive shuffling, the cross over rate (CR), and the scaling factor (F). Since the choice of these parameters could sensibly affect the algorithm performances, some principles and guidelines aimed at supporting the analyst are here discussed. The global optimum searching capability and the convergence speed are very sensitive to the choice of DE control parameters such as scaling factor (F), and crossover rate (CR). Proper values of F and CR are chosen in between 0 and 1. An appropriate value for population size (P) is related to the complexity of the problem.

3.4 Pseudo code for Shuffled Differential Evolution Optimization

The following is the pseudo code for implementing the SDE optimization.

Begin;

Initialize the SDE parameters

Randomly generate a population of solutions (frogs);

For $i = 1$ to SI (maximum no. of generations);

For each individual (frog); *calculate fitness of frogs;*

Sort the population in descending order of their fitness;

Determine the global best frog;

Divide population into m memplexes;

*/*memplex evolution step*/*

For $m = 1$ to m ;

For $e = 1$ to IE (maximum no. of memetic evolutions)

Determine the best frog;

For each frog

Generate new donor vector (frog) from mutation

(using DE/memplexbest/2)

Apply crossover

Evaluate the fitness of new frog;

If new frog is better than old

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Replace the old with new one
End if
End for
End for
End for
/*end of memplex evolution step*/
Combine the evolved memplex;
Sort the population in descending order of their fitness;
Update the global best frog;
End for
End

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3.2. Constraint handling technique

Equality constraint 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 or to overcome this limitations in this paper a novel technique for equality constraint handling is proposed.

IV. SIMULATION RESULTS

The proposed algorithm is implemented using MATLAB. In order to demonstrate the performance of the proposed SDE method, it was tested on two systems. In the next section, ED problem is solved with valve point loading effects considered 3 and 13-unit test systems are compared with well settled nature-inspired and bio-inspired optimization algorithms.

4.1. Three unit thermal system

A system of three thermal units with the effects of valve-point loading was studied in this case. 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. 1. The dispatch results using the proposed method and other algorithms are given in Table 1. The global optimal solution for this test system is 8241.5876 \$/h. From Table 1, it is clear that the proposed method SDE reported the global optimum solution. The mean values also highlighted with red line in the fig 3.

In the Table 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. 5.2 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, is 8241.5876 \$/h and 8240.9518 \$/h respectively. The mean values also highlighted with red line in the fig.4.

Table 1: Comparisons of Simulation results of different methods for 3-unit 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	is 8241.5876

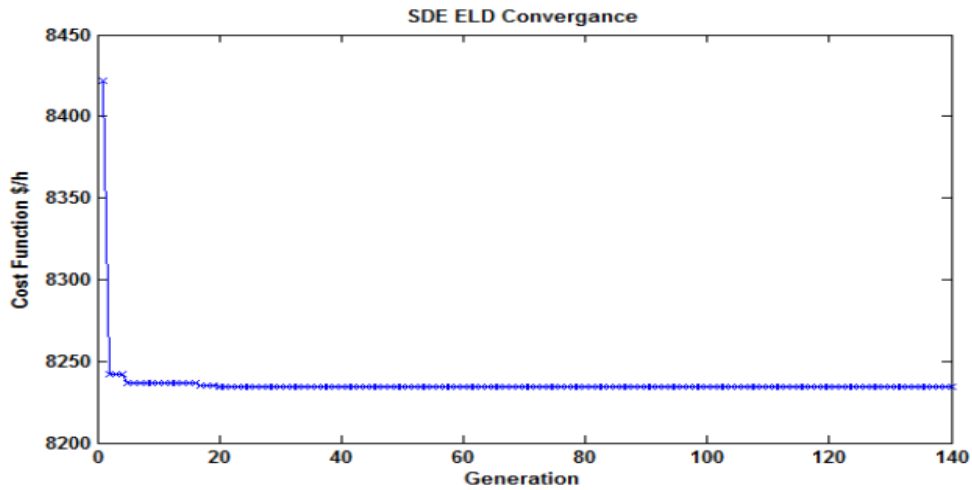


Fig.3. Convergence profile of the total cost for 3-generating units.

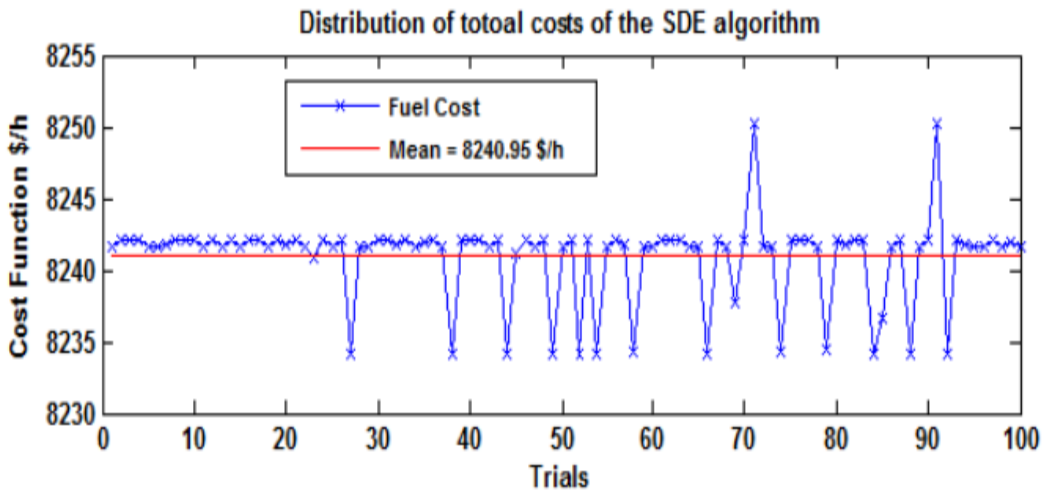


Fig.4 Distribution of total costs of the SDE algorithm for a load demand of 850 MW for 100 different trials for 3-unit case study

4.2. Thirteen unit thermal system

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

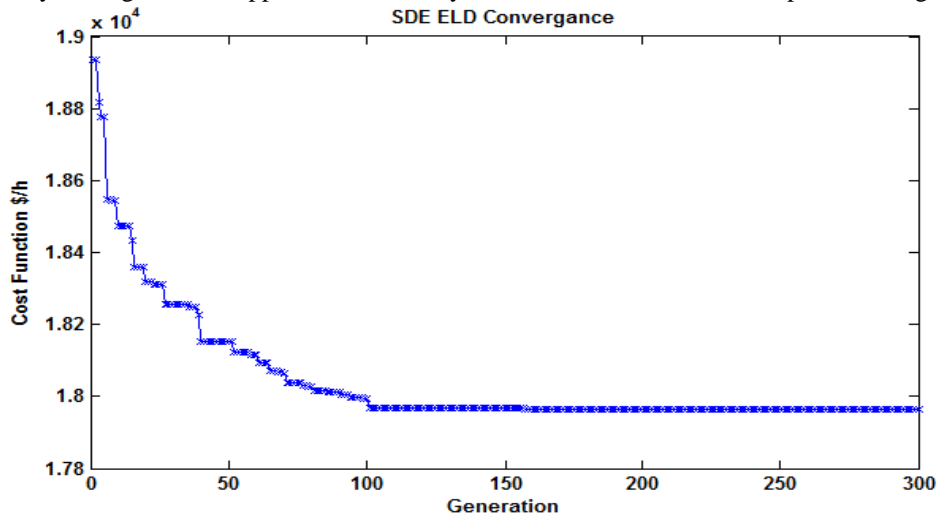


Fig. 5 Convergence profile of the total cost for 13 generating units with $P_D = 1800$ MW

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].

Table 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 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. 5. The results obtained by the proposed methods are compared with those available in the literature as given in Table 2. 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 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. 5.4 shows the variations of the fuel cost obtained by SDE for 100 different runs and convergence results for the algorithms are presented in Table 5.3 for 1800MW load.

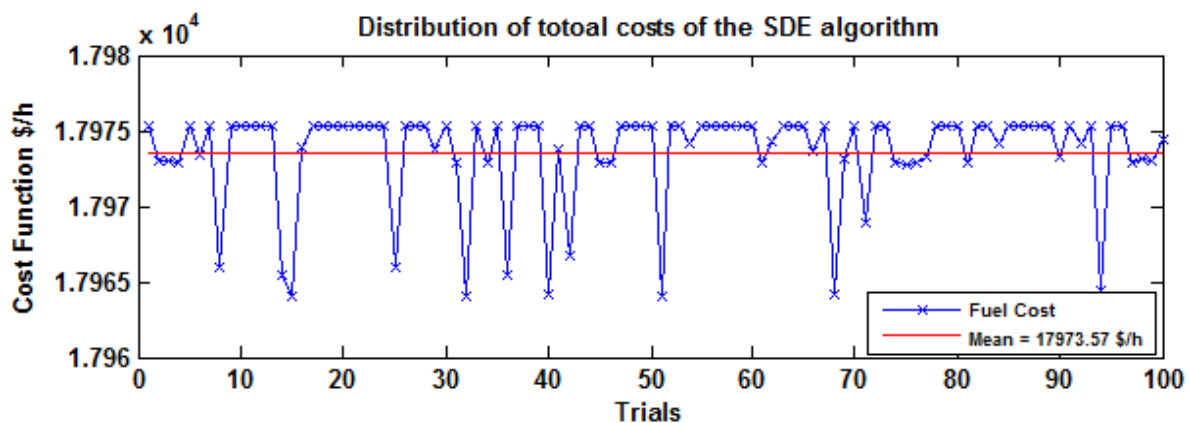


Fig. 6 Distribution of total costs of the SDE algorithm for a load demand of 1800 MW for 100 different trials for 13-unit case study

Fig.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 5.3 for 1800MW load.

Table 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 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.

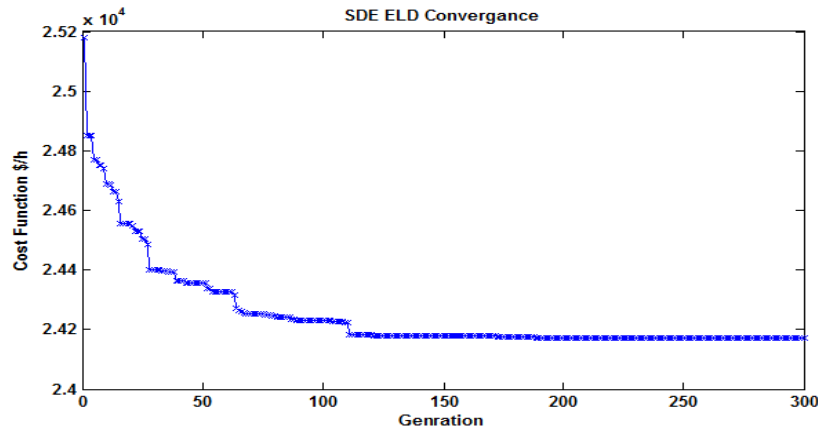


Fig. 7 Convergence profile of the total cost for 13 generating units with $P_D = 2520$ MW

Table 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. 7. The results obtained by the proposed methods are compared with those available in the literature as given in Table 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 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

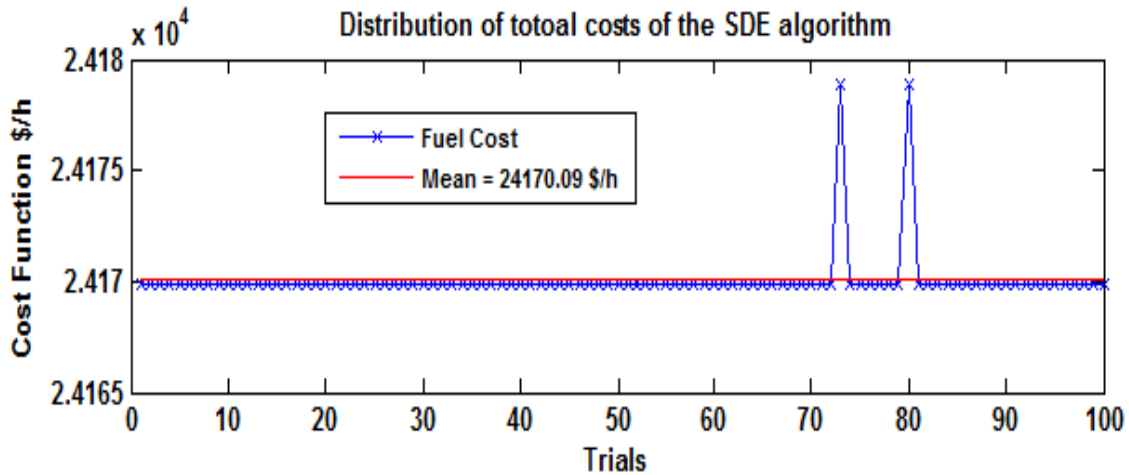


Fig. 8 Distribution of total costs of the SDE algorithm for a load demand of 2520 MW for 100 different trials for 13-unit case study

The results demonstrate that the proposed algorithm outperforms the other methods in terms of better optimal solution. Fig. 8 shows the variations of the fuel cost obtained by SDE for 100 different runs and convergence results for the algorithms are presented in Table 5.3 for 2520 MW load.

Table 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

Table 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. The results obtained by the proposed methods are compared with those available in the literature such as GA_MU [41], HQPSO [42], IGA_MU [48] and FAPSO-NM [20] as presented in Table 2 and Table 4. It can be seen from Table 3 and Table 5, the solution quality of SDE is better than those obtained by other methods. Use of memplex/best mutation scheme often eliminate trapping of SDE algorithm into local minimum and provides global minimum. Analyzing the data it is worth noting as the identified solution satisfies all the system constraints. From the results obtained by SDE method, it is clear that the power balance constraint is satisfied even after considering the 4th decimal.

V. CONCLUSION

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 nonconvex 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 the proposed method succeeded in achieving the goal of reduction generation costs. A 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.

The following are future scope of work with respect to shuffled differential evolution optimization for economic load dispatch problem.

- Considering the spinning reserve capacity and ramp rate limits
- Considering the transmission losses and B co-efficient
- Develop the optimization for optimal power flow with the economic load dispatch
- Improving the shuffled differential evolution optimization for multi objective problem
- Investigating the other performance improvements for shuffled differential evolution

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Authors Profile



Miss. Chandrakala was born in 1990 in Tirumala, (Andhra Pradesh). She received Bachelor of Technology from Yogananda Institute of Technology & Science, Tirupati (Andhra Pradesh) in 2012. She is doing Master of Technology from Audisankara Institute of Technology, Gudur (Andhra Pradesh). She is currently researching in the field of Electrical Power Systems.



Mr. Ramakrishna obtained his B.Tech in Electrical and Electronics Engineering from RGM CET-Nandyal, A.P., in 2009. After the completion of Masters Programme in Power Systems operation & control at **Sri Venkateswara University** Tirupati in 2012, presently he is working as Asst. Professor Dept. EEE, **Audisankara Institute of Technology-Gudur**, Nellore, AP, India.



Mr. Jan Bhasha Shaik was born in Andhra Pradesh, India. He received the B.Tech degree in Electrical and Electronics Engineering from JNT University, Hyderabad in 2004 and M.Tech degree in Power & Industrial Drives from JNT University Kakinada in 2010. He is currently pursuing the Ph.D. degree at the JNT University, Anantapur, Andhra Pradesh, India. He had worked as an Assistant Professor and IEEE student Branch counselor at Hi-Tech College of Engineering, and worked as an Assistant professor at KL University Guntur, AP. Currently He is working as an Associate Professor at Audisankara Institute of Technology, Gudur, AP. He was the academic project coordinator for Under-Graduate & Post Graduate students. His areas of interest are HVDC, FACTS & SMART GRID.