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Evolutionary Programming Techniques for Solving Non-Convex Economic Load Dispatch Problem with Valve-Point Loading Effect

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Abstract: This paper presents three heuristic optimization techniques algorithms like Particle Swarm Optimization (PSO), Teaching-learning Based Optimization (TLBO) and Differential evolution (DE) for solving economic load dispatch (ELD) problem with non-convex/linear fuel cost curves by considering power balance condition, capacity constraints, and valve-point loading effect. These algorithms are used for finding the optimal solution with minimum fuel cost. In this paper, a methodology is used for solving the economic load dispatch that is a combinational unit of three different test systems cases such as 16, 43, and 56 generating units respectively. The three algorithms are presented and described in detailed in this paper. The optimization has been done considering total fuel cost as the fitness function. The results of the Evolutionary programming techniques were compared in terms of fuel cost. The convergence characteristics for all the cases are analyzed and presented in this paper.

Keywords: Economic Load Dispatch (ELD), Particle Swamp Optimization (PSO), Teaching-Learning Based Optimization (TLBO), and Differential evolution (DE)

I. INTRODUCTION

Economic load dispatch (ELD) problem is one of the basic issues in power system operation due to the improvement of the social and industrial sector. So now a day the electrical power market becomes more competitive. Generally, there are so many sources to generate electric power such as thermal power plant, hydroelectric power plant, nuclear power plant, and renewable energy sources. Thermal power plant takes the main role to satisfy the peak load demand. In the case of thermal power plant the generation cost dependents on the fuel cost. In order to overcome the all those problems, the optimal power generation is required which minimize the fuel cost [1]. The primary objective of the ELD is to minimize the total fuel cost of generation while satisfying the operational constraints. In the traditional ELD problem, the cost function for each generator has been presented by a quadratic function and solved using mathematical programming based optimization techniques such as lambda iteration method [2]. base point and participation and gradient-based method, dynamic programming methods. But in reality the input-output characteristics of modern generators non-linear and highly constraints because of valve point effect, generating unit ramp rate limits and prohibited zones[3-6]. To overcome all limitation of the traditional methods recently, heuristic optimization techniques are used such as genetic algorithm (GA), evolutionary programming (EP), particle swarm optimization (PSO), [7] differential evolution (DE), [8] simulated annealing (SA), ant colony optimization (ACO) and artifica1 bee colony (ABC), Teaching-Learning Based Optimization[9] (TLBO), and Differential evolution (DE) have been employed to optimize the ELD problem for better global search abilities against numerical optimization methods[10].

In this paper, have presented the three bio-inspired algorithms such as Particle Swamp Optimization (PSO) Teaching-Learning Based Optimization (TLBO) and Differential evolution (DE) algorithms and to solve ELD problems for three different systems, one consisting of 16 generating units and the others consisting of 43, 56 test system which are generated from 3, 13, and 40 standard test systems respectively for a load demand.

II. PROBLEM FORMULATION

Generally, non-convex ELD problems should consider different operational constraints such as valve-point effects, prohibited zones, ramp rates and multi-fuel options, and power balance constraints. The following objective and constraints are taken into account in the formulation of the ELD problem.

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1) Objective function

The objective of ELD is to minimize the total fuel cost while satisfying all equality and inequality constraints. Generally, the objective function of ELD can be modeled as a quadratic, which can be represented as below equation.

$$Minimize\ F_T = \sum_{i=1}^{N} F_i(P_i) \tag{1}$$

Where $F_i(p_i) = a_i P_i^2 + b_i P_i + c_i$ without valve point loading effect and

$F_i(p_i) = a_i P_i^2 + b_i P_i + c_i + \left| e_i \sin(f_i * (P_i^{min} - p_i) \right|$ With valve point loading effect

Where

F_T= total cost fuel cost of power generation,

F_i =Fuel cost of i^{th} generator

P_i =power output of the i^{th} generator (MW)

$a_i, b_i and\ c_i$ Are fuel consumption cost coefficients of i^{th} generator

e_i and f_i are fuel cost coefficients of the i^{th} with valve point loading effect

N=number of generator

P_i^{min} = minimum power generation limit

The valve-point loading effects will make the cost function non-smooth and increase the number of local optima the fuel cost curve with and without valve-point loading effect which illustrates as in fig1. The minimization of the generation cost is subjected to the following equality and inequality constraints.

A. Equality constraint (power balance equation)

The total generated power should be equal to the sum of the total system demand and transmission loss. The system power balance equation is given a

$$\sum_{i=1}^{N} P_i = P_D + P_L \tag{2}$$

Where $\mathbf{P_D}$= Total power demand (MW)

$\boldsymbol{P_L}$ = Transmission losses (MW)

In this paper, the transmission loss $\boldsymbol{P_L}$of the network is neglected.

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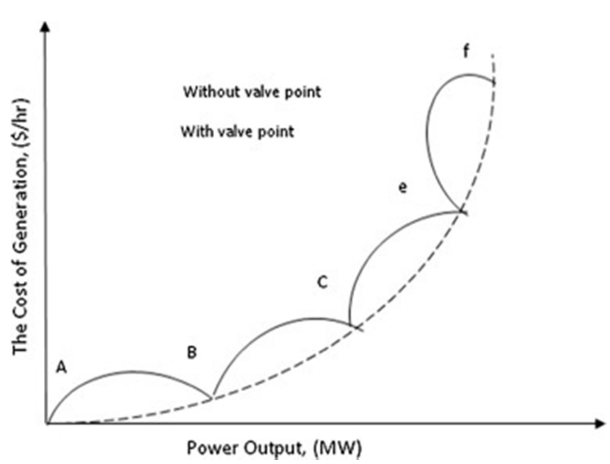

fig1. Valve point loading effect

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B. Inequality Constraints (Generator Capacity Constraints)

The major considered inequality constraint is maximum and minimum limits for power generation. The generation power of each generator should lie between the maximum limit and minimum limit. That represents as below equation.

$$P_i^{min} \leq P_i \leq P_i^{max} \tag{3}$$

Where P_i^{min} and P_i^{max} are the minimum and maximum limits for power output of generator *i*.

III. METHODOLOGY

In this paper, we described three evolutionary algorithms method to solve nonlinear economic load dispatch (ELD) problem with valve-point loading effect. In this section, the basic function of algorithms and the concept behind the algorithms described in detail.

A. Particle Swarm Optimization (Pso)

PSO based operators are exploring the search space. In 1995, Kennedy and Eberhart first introduced the particle swarm optimization method, it is a population-based meta-heuristic that simulates the social behavior of organisms such as fish schooling and bird flocking. PSO, as an optimization tool, provides a population-based search procedure in which individuals called particles to change their positions with time. In a PSO system, particles fly around in a multi-dimensional search space. During the process, each particle adjusts its position according to its own experience, and the experience of neighboring particles, making use of the best position encountered by itself and its neighbors. The swarm direction of a particle is defined by the set of particles neighboring the particle and its historical experience. To get the optimal solution, each particle adjusts their positions by using the following updating equations

$$V_{id}^{(t+1)} = w * V_{id}^{(t)} + C_1 * r_1 * \left(pbest_{id} - X_{id}^{(t)}\right) + C_2 * r_2 * \left(gbest_d - X_{id}^{(t)}\right) \tag{4}$$

$$X_{id}^{(t+1)} = X_{id}^{(t)} + V_{id}^{(t+1)} \tag{5}$$

Where C_1, C_2 are acceleration coefficients, w is inertia weight, r_1 and r_2 are random numbers in the range of [0,1]. $V_{id}^{(t)}$ And $X_{id}^{(t)}$ denote the velocity and position of the particle in d^{th} dimension at t^{th} iteration. $pbest_{id}$ is the value in dimension d of the best parameters combination(a particle) found so far by particle. $pbest_{id} = \langle pbest_{1the}, \dots, pbest_d \rangle$ is called personal best. $gbest_d$ is the value in dimension d of the best parameters combination (a particle)found so far in the swarm. $gbest_d = \langle gbest_1, \dots, gbest_d \rangle$ is represented as the global best. In the search space, particles track the individual's best values and the best global values. The process is terminated if the number of iteration reaches the pre-determined maximum number of iteration.

B. Teaching-Learning Based Optimization (TLBO)

TLBO is based on the relationship between teacher and student in the class. It is a population-based method and it uses a population of solutions to get the global solution. In any optimization algorithm, there are numbers of different design variables. In TLBO design variables are subjects offered to learners and result of learners as considered as the fitness of the population. The algorithm contains two parts they are teacher phase and learner phase. Teacher phase means learning from the teacher and learner phase means learning through the interaction between learners in a class. Implementation of TLBO described below.

1) *Teacher phase:* The teacher tries to improve the mean performance of the class to some extent depending on the capability of the learners. The teacher influences the performance of each student in a random manner for each subject. The best solution in each iteration will be chosen as the teacher $X_{teacher}$. Teacher phase can be represented as followed for i^{th} iteration

$$X_{id}^{(t+1)} = X_{id}^{(t)} + rand() * (X_{teacher} - T_F * M_g) \tag{6}$$

Where $X_{id}^{(t+1)}$ is the new population and $X_{id}^{(t)}$ old population. $X_{teacher}$ is the teacher (best solution), rand () is random number in between 0 and 1. T_F is teaching factor which shouthe ld be either 1 or 2, that is selected randomly. The mean parameter of each subject in the class at each generation g is given as

$$M_g = [m_{1g}, m_{2g} \ldots\ldots m_{dg}] \tag{7}$$

The $X_{id}^{(t+1)}$ is found to be better than $X_{id}^{(t)}$ in i^{th} generation than it replace on $X_{id}^{(t)}$ otherwise, it remains the same.

2) *Learner Phase:* A learner gain knowledge from interaction with some other randomly selected learners, with the help of group discussion, presentation, or some formal communication. Any learner learns from any other learner having better knowledge than him which helps the learner to improve his level of knowledge. For a learner $X_{id}^{(t)}$, randomly select another learner $X_{rd}^{(t)}$ as $i \neq r$.The learner phase can be formulated for i^{th} iteration as followed

$$X_{id}^{(t+1)} = X_{id}^{(t)} + rand() * (X_i^{(t)} - X_r^{(t)}) \quad \text{if } f(X_i^{(t)}) < f(X_r^{(t)}) \tag{8}$$

$$X_{id}^{(t+1)} = X_{id}^{(t)} + rand() * (X_r^{(t)} - X_i^{(t)}) \quad \text{if } f(X_i^{(t)}) > f(X_r^{(t)}) \tag{9}$$

Where rand () denotes a random number in between 0 and 1. The termination condition of algorithm obtained when MAXIT iteration is completed, then the algorithm is stopped, otherwise, repeat from 'Teacher Phase'.

C. Differential evolution

The Differential evolution (DE) is a stochastic population-based algorithm that was used for searching the optimum solution of ELD problems. The advantages of DE 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. Generally, the initialization is performed randomly within constraint boundaries. After initialization DE has three stages to solve the economic load dispatch (ELD) problem such as mutation, crossover, and selection

1) *Mutation:* In mutation each generation and for each individual a donor member using an operator and a donor member is generated by adding a weighted difference of another member. There are several operational strategies for mutation. Commonly used Mutation strategy represented as below

$$V_i^{t+1} = X_{best}^t + F(X_{r1}^t - X_{r2}^t) \tag{10}$$
$$i = 1,2,3\ldots,N_p$$

Where X_{best}^t is best among current population vector and r is random numbea r in between 0 to n. F is scaling factor or of mutation vector, N_p is the population size.

2) *Crossover:* In crossover stage each member of the population is enabled crossover by mating with donor vector to generate a set of trial vector which is calculated equation (11)

$$U_{i,j}^{t+1} = \begin{cases} V_{i,j}^{t+1}, if\ rand(0,1) \leq C_r \\ X_{i,j}^{t+1}, otherwise \end{cases} \tag{11}$$

Where C_r is user supplied crossover rate constant k ∈ {1, 2…..N}

3) *Selection:* The fitness of each individual is calculated and best fitness value is considered to the next generation to get a best the trial vector (X_i^{t+1}) which is represented as equation (12). The value of the cost function in the point u_i^G using the below conditions and based on below condition new population solution selected for next generation.

$$X_i^{t+1} = \begin{cases} u_i^t\ f(u_i^G) \leq f(X_i^t) \\ X_i^t\ f(u_i^G) > f(X_i^t) \end{cases} \tag{12}$$

This evolutionary process consisting of the mutation, crossover and selection stages is repeated over several iterations until getting the optimal solution.

D. Parameters Of Algorithms

The performance of the algorithm depends on the control parameters of algorithms. In this algorithms list of control parameters with approximate values listed in below table

Table1 parameters

Particle Swamp Optimization (PSO), and	$C_1 = 1$, C_2=1,number of population=30,maximum number of iterations=150
Teaching-Learning Based Optimization (TLBO),	TF=0.5, number of population=30, maximum number of iterations=150
Differential evolution (DE)	F=0.9,CR=0.75, number of population=30, maximum number of iterations=150

IV. ALGORITHM STEPS FOR ANALYSIS OF ECONOMIC LOAD DISPATCH (ELD)

In this paper, the three algorithms are applied for solving the nonlinear economic dispatch problem to get optimal power generation. The main steps to calculate the search procedure explained in detailed (consider DE algorithm)

1) *Step 1:* Specify the number of generator units (N), and the generator cost coefficients ($a_i, b_i, and\ c_i$)and valve-point coefficient ($e_i, and f_i$), capacity constraints of all generators [P_i^{min}, P_i^{max}] and load demandP_D. Initialize parameters
2) *Step 2:* An initial population of X is created randomly in N-dimensional search space (number of generating units) which can be denoted as

$$X = \begin{bmatrix} X_1 \\ X_2 \\ \vdots \\ X_p \end{bmatrix} = \left[\begin{pmatrix} x_{1,1} & \cdots & x_{N,1} \\ \vdots & \ddots & \vdots \\ x_{p,1} & \cdots & x_{N,P} \end{pmatrix}\right] \tag{13}$$

where i is represented by N decision variables, such as X_i=$x_{i,1}x_{i,2} \dots \dots . x_{i,N}$. The decision variables for the ED problems are real power generations, so they are used to represent each element of a given population of individual solutions. The equality constraint of generators must be satisfied by the population matrix. The matrix is initialized randomly within the real power operating limits as

$$X_{i,j} = X_{min,N} + rand() * (X_{max,N} - X_{min,N}) \tag{14}$$

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

3) *Step 3:* power balance violations are eliminated by adding a penalty term in their

Fitness function. The fitness function $f(X)$ calculated using equation (15)

$$f(X) = \frac{1}{\mu\left|\sum_{i=1}^{N}(P_i - P_D)\right| + F_T} \tag{15}$$

Where µ is the penalty factor. F_T is the objective of the economic load dispatch (ELD) which is calculated using equation (1)

4) *Step4:* Set ITER = 0 (iteration counter)
5) *Step 5:* Increment the iteration counter i.e., ITER=ITER+1;
6) *Step 6:* Apply the evolution steps of DE, such as mutation, crossover, and selection this is calculated using equations (10) (11) and (12) and new population solution is obtained.
7) *Step 8:* If the maximum number of iterations is not reached, i.e., if,$ITER \geq SI$ go to the steps 5.
8) *Step 9:* Print the best solution and stop.

V. SIMULATION RESULTS AND ANALYSIS

In this paper we use three cases of the combinational test system of three; thirteen and forty have been analyzed, to find the optimal solution with lowest fuel cost with valve-point loading effect. Each case is analysis with three algorithms and results are compared to each other.

A. Case 1: System Consisting Of 16 Thermal Generating Units

In this case, sixteen thermal units with the quadratic cost function are generated by combining three and thirteen unit test system. The expected load demand to meet by all generation units is 2650MW. The system data can be found in the appendix in below which is taken from the [11]. The optimal solution for this test system is reported as 26,302.89 \$/hr. The dispatch results are compared with PSO, TLBO, and DE which is listed in table1 below and cost convergence characteristics is as shown fig2

Table2 16-Unit test system output values with valve pint loading

POWER GENERATION(MW)	PSO	TLBO	DE
P_{g1}	292.180	598.79	119.04
P_{g2}	100.535	500.00	50.000
P_{g3}	337.208	100.00	100.00
P_{g4}	452.381	361.20	527.47
P_{g5}	128.809	360.00	260.84
P_{g6}	301.591	360.00	360.00
P_{g7}	89.7640	60.000	124.01
P_{g8}	134.119	60.000	159.94
P_{g9}	127.841	60.000	161.45
P_{g10}	121.592	60.000	150.89
P_{g11}	118.411	60.000	163.15
P_{g12}	137.451	60.000	147.94
P_{g13}	56.5756	40.000	89.730
P_{g14}	66.2286	40.000	42.720
P_{g15}	89.5046	55.000	95.760
P_{g16}	95.7391	55.000	97.000
Power demand(MW)	2650	2650	2650
Total fuel cost (Rs/hr)	26,290.156	26,547.9416	27,065.5482

B. Case 2: System Consisting Of 43 Thermal Generating Units

In this case, forty-three units with the quadratic cost function are generated by combining three and forty unit test system. The expected load demand to meet by all generation units is 11350MW. The system data can be found in the appendix in below which is taken from [11]. The optimal solution for this test system is reported as 1,38,730.7919 \$/hr. The dispatch results are compared with PSO, TLBO, and DE which is listed in table 3 below and cost convergence characteristics is as shown fig3

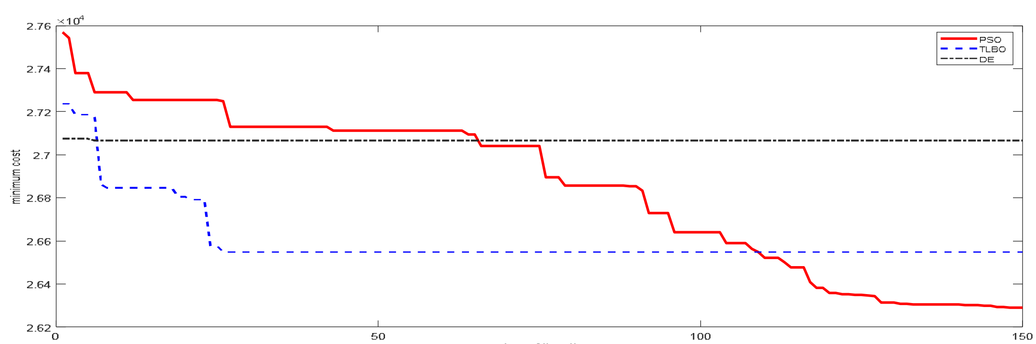

Fig2 Cost convergence characteristics of 16 Unit test system

C. Case 2: System Consisting Of 43 Thermal Generating Units

In this case, forty-three units with the quadratic cost function are generated by combining three and forty unit test system. The expected load demand to meet by all generation units is 11350MW. The system data can be found in the appendix in below which is taken from [11]. The optimal solution for this test system is reported as 1,38,730.7919 $/hr. The dispatch results are compared with PSO, TLBO, and DE which is listed in table 3 below and cost convergence characteristics is as shown fig3

Table3 43-Unit test system output values with valve pint loading

POWER GENERATION(MW)	PSO	TLBO	DE
P_{g1}	600.000	600.000	600.000
P_{g2}	75.2613	99.1790	200.000
P_{g3}	400.000	400.000	400.000
P_{g4}	84.8213	144.000	114.000
P_{g5}	114.000	144.000	114.000
P_{g6}	61.5507	120.000	120.000
P_{g7}	80.2448	190.000	190.000
P_{g8}	79.3870	97.000	97.0000
P_{g9}	69.8664	140.000	140.000
P_{g10}	300.000	144.159	300.000
P_{g11}	210.081	139.919	300.000
P_{g12}	300.000	149.919	300.000
P_{g13}	300.000	259.438	300.000
P_{g14}	248.979	98.9419	110.016
P_{g15}	164.166	375.000	265.712
P_{g16}	287.009	500.000	128.500
P_{g17}	349.952	500.000	130.139
P_{g18}	375.184	500.000	131.245
P_{g19}	500.000	494.182	137.374
P_{g20}	500.000	477.670	130.139
P_{g21}	500.000	477.670	500.000
P_{g22}	539.310	550.000	500.000
P_{g23}	442.851	527.2588	550.000
P_{g24}	426.675	453.8577	467.9039
P_{g25}	55.000	258.9199	259.1394
P_{g26}	543.015	258.9199	550.0000
P_{g27}	55.000	258.9199	550.0000
P_{g28}	55.000	519.7911	550.0000
P_{g29}	357.631	534.8905	550.0000
P_{g30}	16.5256	16.22255	550.0000
P_{g31}	10.5765	14.91999	26.05000
P_{g32}	10.1186	45.16000	21.06900
P_{g33}	48.1708	97.0000	30.94750
P_{g34}	190.000	190.000	97.00000
P_{g35}	186.158	163.8433	190.0000
P_{g36}	60.5331	67.1178	190.0000
P_{g37}	91.8540	200.000	190.0000
P_{g38}	151.522	200.000	200.0000
P_{g39}	175.858	200.000	200.0000
P_{g40}	110.000	32.1178	200.0000
P_{g41}	96.6910	110.000	110.0000
P_{g42}	110.000	110.000	110.0000
P_{g43}	550.000	550.000	550.0000
POWER DEMAND (MW)	11350.00	11350.00	11350.00
COST (Rs/Hr)	138730.79	144389.0381	136573.0503

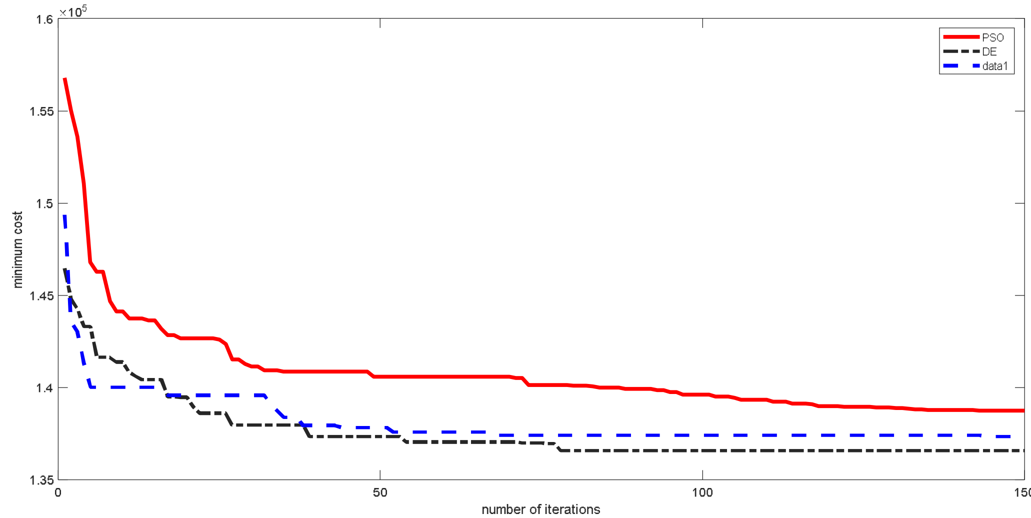

Fig3 Cost convergence characteristics of 43 Unit test system

D. *Case 3: System Consisting Of 56 Thermal Generating Units*

In this case, fifty-six three units with the quadratic cost function are generated by combining three, thirteen and forty unit test system The expected load demand to meet by all generation units is 11350MW. The system data can be found in the appendix in below which is taken from[11]. The optimal solution for this test system is reported as 1,52,033.60677 $/hr. The dispatch results are compared with PSO, TLBO, and DE which is listed in table4 below and cost convergence characteristics is as shown fig4

Table4 56-Unit test system output values with valve pint loading

UNIT	PSO	TLBO	DE
P_{g1}	370.7682	600.0000	600.0000
P_{g2}	94.3090	102.8526	200.0000
P_{g3}	400.0000	398.6841	400.0000
P_{g4}	680.0000	665.4527	680.0000
P_{g5}	360.0000	360.0000	360.0000
P_{g6}	360.0000	360.0000	360.0000
P_{g7}	180.0000	180.0000	180.0000
P_{g8}	80.6973	180.0000	180.0000
P_{g9}	61.7646	180.0000	180.0000
P_{g10}	180.0000	180.0000	180.0000
P_{g11}	60.0000	180.0000	180.0000
P_{g12}	140.4116	180.0000	180.0000
P_{g13}	130.9342	120.0000	120.0000
P_{g14}	73.7083	120.0000	106.5500
P_{g15}	86.0890	120.0000	120.0000
P_{g16}	55.0000	120.0000	91.0940
P_{g17}	36.0000	114.0000	114.0000
P_{g18}	36.0000	114.0000	98.0909
P_{g19}	60.0000	120.0000	120.0000
P_{g20}	166.8223	190.0000	174.2069
P_{g21}	57.3665	97.000	60.0000
P_{g22}	103.1561	140.0000	140.000
P_{g23}	246.7134	257.5224	212.1483
P_{g24}	285.6071	209.9285	294.0311
P_{g25}	300.0000	273.4410	300.0000

P_{g26}	294.5018	263.6534	212.0322
P_{g27}	375.0000	94.9484	130.5631
P_{g28}	333.7189	97.3848	97.2834
P_{g29}	142.5782	131.6347	145.4148
P_{g30}	500.0000	149.3549	128.0568
P_{g31}	356.7579	222.5020	194.1654
P_{g32}	205.4976	253.4946	142.9923
P_{g33}	409.8413	461.0768	494.5036
P_{g34}	293.5827	432.5063	500.0000
P_{g35}	542.8281	424.5633	500.0000
P_{g36}	468.1670	540.1180	452.5749
P_{g37}	495.8552	442.1932	257.2834
P_{g38}	411.0000	261.9778	257.2834
P_{g39}	546.1186	496.1674	550.0000
P_{g40}	550.0000	421.2119	550.0000
P_{g41}	550.0000	466.1607	550.0000
P_{g42}	550.0000	465.3966	361.6186
P_{g43}	21.6468	34.5292	13.2834
P_{g44}	10.0000	32.8170	13.2834
P_{g45}	10.0000	10.9484	31.8487
P_{g46}	47.0000	97.0000	97.0000
P_{g47}	190.000	190.0000	190.000
P_{g48}	141.9280	190.0000	169.6512
P_{g49}	81.4377	190.0000	187.0850
P_{g50}	142.1179	200.0000	200.0000
P_{g51}	186.0013	200.0000	200.0000
P_{g52}	138.9260	200.0000	145.4258
P_{g53}	41.8278	110.0000	105.5019
P_{g54}	67.9885	110.0000	99.9214
P_{g55}	84.9826	110.0000	110.000
P_{g56}	382.3487	287.4788	382.9154
POWER DEMAND (MW)	13150.000	13150.000	13150.000
COST (Rs/Hr)	157711.3452	154193.6778	152033.60677

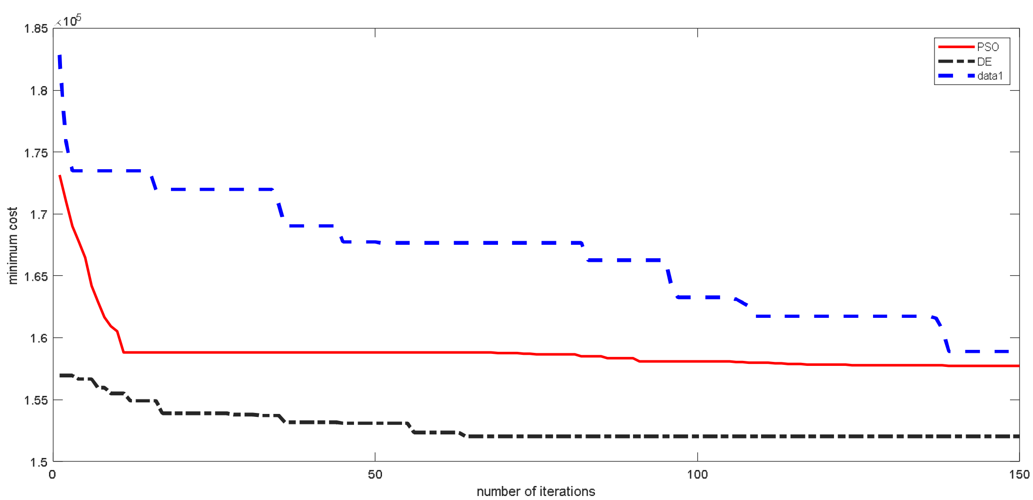

Fig4 Cost convergence characteristics of 56 Unit test system

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VI. CONCLUSION

In this paper economic load dispatched problem has been solved using three algorithms Particle Swarm optimization (PSO), Teaching-Learning Based Optimization (TLBO), Differential evolution (DE) The study has been done for three different combinational systems, one consists of 16 generating units, and the others consisting of 43 and 56, respective for different load demand. The performance analysis has been carried out when transmission losses have been neglected. In this paper we present, analysis using PSO, TLBO, and DE for economic load dispatch solution for all the three systems under consideration for different load demand has been obtained. The results three cases Generating units systems then compared with one other. So, by observing the result obtained using PSO, TLBO, and DE algorithms. DE gives better results compared to the remaining two algorithms. So, finally, it can be analyzed that applying PSO, TLBO, and DE to economic load dispatch solution optimal and reliable result are obtained.

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APPENDIX

Generator 3 unit	$P_{min}(MW)$	$P_{max}(MW)$	a ($/MW	b ($/MW)	c ($)	e (MW)	f
1	100	600	0.001562	7.92	561	300	0.0315
2	50	200	0.004820	7.97	78	150	0.063
3	100	400	0.001940	7.85	310	200	0.042
13 unit	$P_{min}(MW)$	$P_{max}(MW)$	a	b	c	e	f
4	00	680	0.00028	8.10	550	300	0.035
5	00	360	0.00056	8.10	309	200	0.042
6	00	360	0.00056	8.10	307	200	0.042
7	60	180	0.00324	7.74	240	150	0.063
8	60	180	0.00324	7.74	240	150	0.063
9	60	180	0.00324	7.74	240	150	0.063
10	60	180	0.00324	7.74	240	150	0.063
11	60	180	0.00324	7.74	240	150	0.063
12	60	180	0.00324	7.74	240	150	0.063
13	40	120	0.00284	8.6	126	100	0.084
14	40	120	0.00284	8.6	126	100	0.084
15	55	120	0.00284	8.6	126	100	0.084
16	55	120	0.00284	8.6	126	100	0.084
40 unit	$P_{min}(MW)$	$P_{max}(MW)$	a	b	c	e	f
17	36	114	0.00690	6.73	94.705	100	0.084
18	36	114	0.00690	6.73	94.705	100	0.084

19	60	120	0.02028	7.07	309.54	100	0.084
20	80	190	0.00942	8.18	369.03	150	0.063
21	47	97	0.0114	5.35	148.89	120	0.077
22	68	140	0.01142	8.05	222.33	100	0.084
23	110	300	0.0035.7	8.03	287.71	200	0.042
24	135	300	0.00492	6.99	391.98	200	0.042
25	135	300	0.00573	6.60	455.76	200	0.042
26	130	300	0.00605	12.9	722.82	200	0.042
27	94	375	0.00515	12.9	635.20	200	0.042
28	94	375	0.00569	12.8	654.69	200	0.042
29	125	500	0.00421	12.5	913.40	300	0.035
30	125	500	0.00752	8.84	1760.4	300	0.035
31	125	500	0.00708	9.15	1728.3	300	0.035
32	125	500	0.00708	9.15	1728.3	300	0.035
33	220	500	0.00313	7.97	647.85	300	0.035
34	220	500	0.00313	7.95	649.69	300	0.035
35	242	550	0.00313	7.97	647.83	300	0.035
36	242	550	0.00313	7.97	647.81	300	0.035
37	254	550	0.00298	6.63	785.96	300	0.035
38	254	550	0.00298	6.63	785.96	300	0.035
39	254	550	0.00284	6.66	794.53	300	0.035
40	254	550	0.00284	6.66	794.53	300	0.035
41	254	550	0.00277	7.10	801.32	300	0.035
42	254	550	0.00277	7.10	801.32	300	0.035
43	10	150	0.52124	3.33	1055.1	120	0.077
44	10	150	0.52124	3.33	1055.1	120	0.077
45	10	150	0.52124	3.33	1055.1	120	0.077
46	47	97	0.01140	5.35	148.89	120	0.077
47	60	190	0.00160	6.43	222.92	150	0.063
48	60	190	0.00160	6.43	222.92	150	0.063
49	60	190	0.00160	6.43	222.92	150	0.063
50	90	200	0.0001	8.95	107.87	200	0.042
51	90	200	0.0001	8.62	116.58	200	0.042
52	90	200	0.0001	8.62	116.58	200	0.042
53	25	110	0.0161	5.88	307.45	80	0.098
54	25	110	0.0161	5.88	307.45	80	0.098
55	25	110	0.0161	5.88	307.45	80	0.098
56	242	550	0.00313	7.97	647.83	300	0.035