Hybrid Optimization Approaches to Economic Load Dispatch Problems – A Comparative Study

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Abstract - *The main objective of the Economic Load Dispatch (ELD) problem is to minimize the total fuel cost by considering both the equality and inequality constraints. To obtain the aforesaid objective, all the online generators are to be operated in optimum power simultaneously. Many optimization techniques have been formulated in the past decades for solving various types of ELD problems. Hybrid optimization technique is the combination of two or more optimization algorithms, in which the output depends upon the best qualities of the combined algorithms. A study on various hybrid optimization techniques is carried out in this article.*

Key Words: Economic load dispatch - Equality constraints - Fuel cost - Inequality constraints – Optimization techniques.

1. INTRODUCTION

Nowadays, managing the electrical power generating system is the major concern. The demand for the consumption of power increases day by day and this binds the optimal combination of operating the generating units. The ELD problem comprises the pre-dispatch and online dispatch problems: pre-dispatch problem requires the optimal selection of the generating units and the online dispatch problem is to reduce the total cost required for the dynamic requirements of the system. Consider a system with n power generating units. The objective function of the ELD problem is given in equation 1. Figure 1 represents the economic load dispatch considering the valve-point effects and no valve-point effects.

$$F_t = \sum_{i=1}^{n} a_i P_i^2 + b_i P_i + c_i \qquad (1)$$

n refers to the total number of generation units,

a_i, b_i, c_i - the cost coefficients of i^{th} power generation unit

P_i - the output of i^{th} power generation unit

C_i - the cost function of i^{th} generating unit and i = 1, 2 … n.

2. Hybrid approaches to economic load dispatch problems

Many optimization techniques have been proposed from the past for solving the ELD problems. Though the algorithms gave best results as per their characteristics, few limitations exists which reduces the performance of the system chosen.

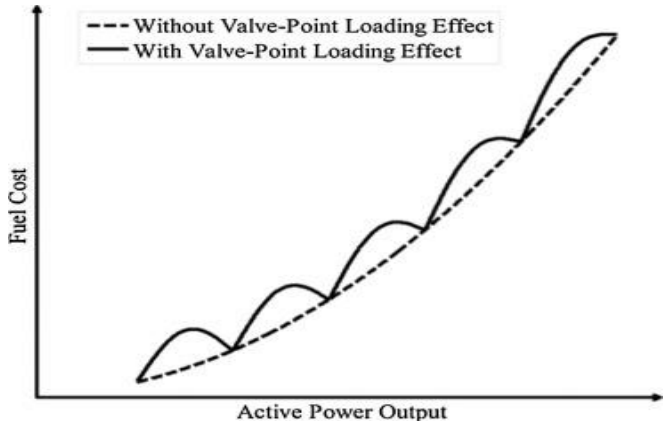

Fig. – 1: Representation of ELD considering VPL and not considering VPL

To overcome the limitations of the classical optimization techniques, many hybrid approaches has been proposed. In this section, different hybrid methods are analyzed. The purpose of finding the hybrid combination is to generate high quality solution with stable convergence, flexibility and robustness and less computational time compared to other soft computing techniques.

2.1 Particle Swarm Optimization—Direct Search Method (PSO-DS):

The PSO-DS technique (Victoire, et al., 2003)[1] was formulated to solve the ELD problem, to demonstrate the flexibility and the efficiency. The PSO-DS was tested in different scenario and the results are tabulated in Table 1. It is found that the generating units were expected to supply the load demands of 2400 MW, 2500 MW, 2600 MW and 2700 MW. In case of scenario 2, the PSO-DS method is compared with Numerical Method (NM), Enhanced Lagrangian Neural Network (ELNN) method, GA, and EP. The authors ended up with the obtained results that the PSO-DS outperforms the other algorithms compared.

Table -1: Output for the proposed PSO-DS method with P_D=2520 MW with 13 units

Generator	Cost / unit generation (MW)			
	PSO-DS	GA	SA	GA-SA
z_1	628.3094	628.32	668.40	628.23
z_2	298.9996	356.49	359.78	299.22

z_3	298.8181	359.43	358.20	299.17
a_1	159.7441	159.73	104.28	159.12
a_2	159.5509	109.86	60.36	159.95
a_3	159.1718	159.73	110.64	158.85
a_4	159.5712	159.63	162.12	157.26
b_1	159.5940	159.73	163.03	159.93
b_2	159.4003	159.73	161.52	159.86
b_3	113.6156	77.31	117.09	110.78
c_1	113.2250	75.00	75.00	75.00
c_2	55.0000	60.00	60.00	60.00
c_3	55.0000	55.00	119.58	92.62
Total cost ($/h)	24182.55	24398.23	24970.91	24275.71

Table -2: Output for the proposed PSO-DS method with 10 units for various power demands

P_D(MD)	Fuel Cost ($/h)				
	PSO-DS	NM	ELNN	GA	EP
2400	481.72	488.50	481.74	482.00	481.79
2500	526.24	526.70	526.27	526.24	526.24
2600	574.03	574.41	574.40	574.39	574.38
2700	625.18	623.88	623.81	623.81	623.81

2.2 Chaotic Particle Swarm Optimization—Quasi-Newton Implicit Filtering Algorithms (PSO or Chaotic PSO–IF):

The application of hybrid chaotic PSO-IF method (Coelho, et al., 2007)[2] to ELD problems was examined. Implicit filtering is the Quasi-Newton DS method which generalizes the gradient projection algorithm. To avoid the local minima, the step sizes are identically changed, which attributed to low-amplitude oscillations. In this approach, all possible state is visited only once called chaotic motion. The authors deliver the report on a test case which involves 13 thermal units of generation along with VPL. In the reported test case, the total load demand was 1800MW. The outcomes are illustrated in table 3.

Table -3: Convergence results for 50 runs

Optimization method	Mean time (s)	Minimum cost($/h)	Mean cost ($/h)	Maximum cost ($/h)
IF	1.4	18812.3852	18962.0139	19111.6426
PSO	2.6	18874.7634	19159.3967	19640.4168
Chaotic PSO	3.3	18161.1013	18809.8275	19640.7556
PSO-IF	17.8	18605.1257	18854.1601	19111.6426
Chaotic PSO-IF	15.3	17963.9571	18725.2356	19057.2663

2.3 Evolutionary Programming—Efficient Particle Swarm Optimization (EP-EPSO):

The joint performance of EP and EPSO was formulated by (Pandian, et al., 2010)[3] to solve the economic load dispatch problem with transmission losses. In the EP sub-problem, a new population is formed by the addition of Gaussian random number with zero mean and fixed standard deviation. Among all the generated new solutions, stochastic tournament method is implemented for the selection of best solution. The basic PSO is modified by updating the position, velocity, P_{best} and g_{best} values by satisfying the required constraints in a newer way. The EP-EPSO method is tested with 40-unit system considering two different problems. The proposed method outperforms when compared with Neural Network (NN), EP, EPSO and hybrid NN-EPSO as shown in Table 4.

Table -4: Simulation results for 40 generating units

Method	Cost ($/h)	Simulation time (s)
NN	146069.74	28.07
EPSO	130330.36	7.232
EP	143799.00	9.242
NN-EPSO	130328.32	8.3529
EP-EPSO	130227.33	7.7590

2.4 Genetic Algorithm—Particle Swarm Optimization (GA-PSO):

The formulation of hybrid GA-PSO was proposed by (Younes, et al., 2011)[4] to solve the ELD problems. The execution of both algorithms is carried out simultaneously. Among all those individuals, the value with larger fitness is selected. The proposed approach is carried out with five different load demand situations for IEEE 25-bus system and the obtained results are compared with the classical optimization methods viz., Broyden-Fletcher-Goldfarb-Shanno (BFGS) and some intelligent methods such as Binary-Coded Genetic Algorithm (BCGA), Real-Coded Genetic Algorithms (RCGA), and PSO. The comparative results are tabulated in the Table 5.

Table -5: Simulation results for IEEE 25-bus system

P_D(MW)	BFGS	BCGAs	RCGAs	PSO	GA-PSO
P_1	211.30	206.72	213.68	197.45	211.54
P_2	126.30	121.64	127.46	114.93	122.46
P_3	151.29	151.82	141.93	168.29	140.117
P_4	71.24	33.21	29.53	29.08	27.358
P_5	211.31	358.05	258.86	259.29	267.514
Total cost($/h)	2029.3	2011.0	2010.8	2099.00	2007.44

2.5 Fuzzy Adaptive Particle Swarm Optimization (FA-PSO):

The FA-PSO hybrid optimization method was proposed by (Soni, et al., 2012)[5] which is more suitable for solving ELD problems. PSO often causes the long-time stagnation issue. To eliminate the aforesaid issue, fuzzy technique is introduced in PSO. Here, the learning factors (c1, c2) and the inertia weight (w) are the parameters to be adjusted with respect to the input variables. The bounded values for (w) is given by 0.2 ≤ w ≤ 1.2, for c1 it is 1≤ c1 and for c2 it is c2≤ 2. Table 6 gives the performance values for FA-PSO algorithm. The proposed hybrid algorithm was tested with 6 generators, 46 transmission lines and 26 buses with 1263 MW demand.

Table -6: Test results for IEEE 6 unit system with P_D = 1263 MW

Method	Best Cost ($)	Worst cost ($)	Average Cost ($)
FA-PSO	15445.24	15451.60	15448.05
SOH-PSO	15446.00	15451.17	15450.3
Simple PSO	15466.61	15451.7	15450.3

2.6 Artificial Bee Colony—Particle Swarm Optimization (ABC-PSO):

The combined ELD problem involving ABC and PSO technique was formulated by (Manteaw, et al., 2012)[6]. The main objective was combined using weighting function and the best objective was determined by cardinal priority ranking method. Initially ABC is executed till the terminal criterion is reached and the best solutions are generated. After this execution, the best individual solutions are fed as input to PSO. This hybrid approach was tested for IEEE 10-generator system with 2000 MW load demand. The comparison with the other methods such as DE, Non-sorting Genetic Algorithm (NSGA) and Strength Pareto Evolutionary Algorithm (SPEA) reveals that the proposed hybrid approach outruns the existing algorithms as given in Table 7.

Table -7: Test results for IEEE 10 unit system with P_D= 2000 MW

	ABC-PSO	DE	NSGA-II	SPEA-II
FuelCost ($/h)	113,420	113,480	113,540	113,520

2.7 Simulated Annealing—Clonal Selection Algorithm (SA-CSA):

A hybrid approach namely Simulated Annealing Clonal Selection Algorithm (SA-CSA) was proposed by (Amjadi, et al., 2010)[7]. The selection step of CSA consists of two levels of selection: the initial is done by CSA and then using SA. The selection of antibodies from the whole population is proceeded with the help of CSA. The values of initial population are compared with the previous level. After CSA, the SA is applied for the purpose of selection with the help of the following equation:

$$P(t+1) = \begin{cases} P_i'(t), F(P_i'(t)) < F(P_i(t)) \\ P_i'(t), F(P_i'(t)) > F(P_i(t) h(P_i(t), P_i'(t) > rand \\ P_i(t), otherwise \end{cases}$$

$$h(P_i(t), P_i'(t) = exp\left[\frac{F(P_i(t)) - F(P_i'(t))}{F(P_i(t))} / T\right]$$

$$T(iter+1) = \propto T(iter) and\ T(0) = T_0$$

In the above equation, the difference between the parent and the offspring objective function has been chosen for the eliminating the effect of diversity of the objective functions. The authors tested this hybrid approach with 10-unit system and a load of 2700 MW. The proposed method is validated with the other contemporary methods and it reveals the performance. Table 8 gives the simulation results of SA-CSA method.

Table -8: Test results for IEEE 10 unit system with P_D= 2700 MW

Methods	Total generation cost ($/h)		
	Best	Average	Worst
CGA-MU	624.7193	627.6087	633.8652
IGA-MU	624.5178	625.8692	630.8705
*PSO-LRS	624.2297	625.7887	628.6214
**NPSO-LRS	624.1273	624.9985	626.9981
***CBPSO-RVM	623.9588	624.0816	624.2930
SA-CLONAL	623.8143	623.8356	623.8480

(*PSO-LRS - Particle Swarm Optimization; Local Random Search, *NPSO-LRS-New PSO Local Random Search; ***CBPSO-RVM-Combined PSO-Real Value Mutation)

2.8 Bacterial Foraging-Differential Evolution (BF-DE):

The combination of BF and DE algorithms referred to as Chemotactic Differential Evolution (CDE) algorithm was presented by (Biswas, et al., 2009) [8]. Generally Bacterial Foraging performs the local search based on Gradient Descent method. The author has incorporated into DE, which is an adapted form of chemotactic step. Until the population converges to local optima, the global optimum point may not be approached. Addition of new individuals or population takes place, but due to stagnant condition DE will not proceed to attain a better solution. To improve the convergence characteristics of the classical DE, foraging random walk vector has been introduced in this hybrid approach. On successful implementation, BF breaks the dead loop and also helps to jump from the local minima. The proposed method has been simulated with 6-unit system with P_D=1263 MW and outruns are tabulated in the Table 9.

Table -9: Simulation results for IEEE 6 unit system with P_D= 1263 MW

	BF-DE	PSO	GA	NPSO -LRS	CPSOI
Minimum cost	15444.1564	15450	15459	1540	15447

2.9 Genetic Algorithm—Active Power Optimization (GA-APO):

A new hybrid approach combining GA and APO was proposed by (Malik, et al., 2006)[9], to solve the ELD problems along with VPL. On combining the GA and APO, it is capable of fine tuning the results produced by GA. APO is formulated with the technique of storage optimization and classical linear system solution method. In this approach, GA acts as a global optimizer which produces the near optimal solution and APO works on this schedule, where the power output of the generating buses is replaced. This approach mainly aims at reducing the cost and also producing the optimum generation schedule. This hybrid approach is performed in a framework referred to as PED Frame under visual C environment. Through this PED frame, the input curve (cost) and other ELD specific information can be given and at the other end, the output can be obtained in a standard format. The implementation was done with three different test systems viz., 3 machines 6 bus system, IEEE 5 machine 14 bus system, and IEEE 6 machine 30 bus system. Table 10 shows the comparison results between GA and GA-APO. To convert the quadratic convex cost curve into non-convex cost curves, the VPL effects are introduced into the existing system.

Table -10: Simulation results for 3, 5 and 6 machine IEEE systems

System	Cost of GA	Cost of GA-APO
IEEE 6 Bus 3 machine system – P_D=210MW	3463.37	3205.99
IEEE 14 Bus 5 machine system – P_D=259MW	1012.44	905.54
IEEE 30 Bus 6 machine system - P_D =283.4 MW	1117.13	984.94

2.10 Differential Evolution—Biogeography-Based Optimization (DE-BBO):

A hybrid DE-BBO method was formulated by (Bhattacharya, et al., 2010) [10] to solve the ELD problem that includes transmission losses and constraints such as ramp rate limits, valve-point loading and prohibited operating zones. Though DE yields many advantages, one of the major disadvantages is that it cannot map all the unknown variables together when the system complexity and size increases. The quality of the good fitness value often gets decreased due to the crossover operation in DE. When BBO is concerned, there is no crossover stage and so the solutions get mature gradually and lead to the operation of migration. In this hybrid approach, development of new features takes place due to the mutation process by DE and migration process by BBO. As both the processes are involved, the good solutions are less destroyed. The results obtained are compared for a system for 10 generating units with other hybrid approaches. Table 11 gives the highest, lowest and the mid values of the proposed and the other hybrid approaches.

Table -11: Simulation results for IEEE 10 unit system

Methods	Generation cost($/h)		
	Max.	Min.	Average
DE-BBO	605.62	605.62	605.63
NPSO-LRS	626.99	624.13	624.99
PSO-LRS	628.32	624.23	625.79
IGA-MU	630.87	624.52	625.87
CGA-MU	633.87	624.72	627.61

2.11 Hybrid Immune Genetic Algorithm (HIGA):

HIGA was proposed by (Hosseini, et al., 2012) [11] for solving the ELD problems. Immune Algorithm and Genetic Algorithm (GA) combine together to form HIGA. The outrun of the initial solution created by Immune Algorithm is iteratively improved by affinity factor, hyper-mutation operator and clonal selection. The hypermutation in HIGA is similar to that of mutation operator in GA. The probability of mutation is inversely proportional to the affinity factor of the solution. Thus if the affinity factor is low, it will be still mutated to improve the solution space and vice-versa. The crossover operator is used to propagate the attributes of high-quality solutions among others. Table 12 and 13 represents the cost comparisons of HIGA optimization for 6 unit and 40 unit power generation systems respectively.

Table -12: Simulation results for 6 unit system with P_D= 1263 MW

	BFO	PSO	NPSO-LRS	GA	HIGA
Total cost	15443.85	15450.14	15450.00	15457.96	15443.10

Table -13: Simulation results for 40 unit system with P_D = 10500 MW

	DE-BBO	BBO	QPSO	HIGA
Total cost	121420.90	121426.95	121448.21	151416.94

2.12 Fuzzified Artificial Bee Colony Algorithm (FABC):

The FABC algorithm was demonstrated by (Koodalsamy, et al., 2013) [12] for solving multi-objective ELD problem. This approach minimizes the energy availability, cost of emission and also fuel cost reduction simultaneously by satisfying load demands and specific constraints. With definite number of bees, ABC functions to locate the food sources in a multidimensional search space. With each generation cycle, the best result is chosen from the Pareto optimal set using fuzzy fitness. The best and the final solution correspond to the maximum value in the entire search space implying food sources with highest quality of nectar information. The authors tested the proposed algorithm for IEEE 30 bus system with two different load conditions (2.834 MW and 2.8339 MW). Table 14 gives the comparison with the other reported methods.

Table -14: Simulation results for IEEE 6 unit system with P_D=1263 MW

Load	2.834 MW		2.8339 MW			
Method	MOPSO	FABC	NSGA	MOHS	MBFA	FABC
Total Cost	938.91	938.75	938.46	939.92	938.33	938.24

2.13 Firefly Algorithm-Ant Colony Optimization (FFA-ACO):

A modern approach involving FFA and ACO algorithm was proposed by (Younes, et al., 2013) [13]. In this approach, initial population n of fireflies x_i is generated. The objective function is used to determine the light intensity of the firefly. As and when the firefly *i* moves towards *j*, the new possible solutions or attractiveness of the fireflies are evaluated. The best solutions are passed as initial points of the fireflies. According to the scheduled activities, the response of the ant's is compared and the best solution is found by the communication with the best ant response. The FFA-ACO algorithm is tested with modified IEEE 30 bus system consisting of 6 generators. The power demand is 283.40 MW. Table 15 shows the comparison with the other approaches.

Table -15: Test results for IEEE 6 unit system with P_D=283.40 MW

	MDE-OPF	PSO	ACO	FFA	FFA-ACO
Cost($/h)	802.62	801.77	801.77	801.01	800.79
Time (s)	23.07	16.26	14.97	13.83	10.73

2.14 Particle Swam Optimization—Gravitational Search Algorithm (PSO-GSA):

The PSO-GSA was proposed by (Dubey, et al., 2013)[14] to solve the ELD problems. The main aim of this approach is to combine the social behaviour (gbest) in PSO along with local search capability of GSA. In this approach, all the agents are initialized randomly. After its initialization, the force acting on agents, mass and acceleration are calculated. The best fitness function will be updated after each iteration. The algorithm was tested for a 6 unit generator system with 1263 MW total demand. The effectiveness of the algorithm was validated by optimizing the ED considering the non-equality constraints like ramp rate limits and generator prohibited zones. Table 16 presents the comparison values with nine other optimization methods.

Table -16: Simulation results for IEEE 6 unit system with P_D=1263 MW

Methods	Min. generation cost($/h)	Time/iter(s)
PSO	15450.00	14.89
GA	15459.00	41.58
NPSO-LRS	15450.00	-
ABF-NM	15443.82	-
DE	15449.77	0.0335
SOH-PSO	15446.02	0.0633
HHS	15449.00	0.14
BBO	15443.09	0.0325
Hybrid SI-based HS	15442.84	0.9481
PSO-GSA	15442.39	0.0420

2.15 Particle Swarm Optimization—Ant Colony Optimization Algorithm (PSO-ACO):

In the above subsections, some hybrid methods have been discussed that are used to obtain the optimized solution for ELD problems. The researches confirm that the PSO method itself can be used as a powerful and useful technique for obtaining the optimal solution. If the global best and local best positions are identical, the algorithm might get stuck into local optima. It is a major drawback of PSO. To eliminate this drawback, many hybrid methods combining PSO with other global optimization algorithms like GA, IF, EP, FA, ABC, GSA has been formulated. In addition to above formulated hybrid approaches, a new hybrid PSO is suggested by the author (Santra, et al., 2016) [15]. This approach combines the PSO and ACO algorithm together. Here new solutions or members can be generated at each iteration using PSO and then ACO can be applied for the fine-tuning of the members.

3. DISCUSSION

Conventional methods like lambda iteration method, Lagrange's method and Taguchi method provides the optimum solution based on a traditional approach of simple iterative procedures and the major drawbacks of these approaches are high computational time, local minima problems and single optimum solutions. Heuristic and meta-heuristic algorithms (random search techniques) like GA, PSO, ACO, ABC, FA, DS, BBO, GSA, CSA, SA, DE and BF provides better solutions due to their global optimum search techniques and considering several parameters of the natural behaviour of living beings. These methods are so popular due to their large solution space, quick convergence criteria and global optimum solutions. Hybrid optimization techniques are developed by combining the best aspects of two or more algorithm parameters from various optimization techniques. Examples of hybrid algorithms are PSO-DS, PSO-IF, EP-EPSO, GA-PSO, FA-PSO, ABC-PSO, SA-CSA, BF-DE, GA-APO, DE-BBO, HIGA, FABC, FFA-ACO, PSO-GSA. Due to the combination of best aspects of two or more algorithms, these methods eliminate the drawbacks of earlier methods and provide global optimum solutions with multi objectives.

4. CONCLUSION

With evolving of new and hybrid optimization methods, ELD problem from small scale to large scale systems has been optimized to a greater extent. Considering the recent and past researches, it is inferred that there is a large and enough scope for research to address the challenges related to power systems. Some of these challenges are: (i) Optimal Power Flow(OPF) problem, (ii) optimization of multiple objectives like Reliable Emission and Economic Dispatch (REED) problem and Combined Economic and Emission Dispatch (CEED) problem, (iii) Extended ELD problem for large number of units(40–90 units) and for more complex objective and constraint function (like exponential function and higher order polynomial).

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