Study of Economic Load Dispatch by Various Hybrid Optimization Techniques

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Abstract The economic load dispatch (ELD) is one of the most complex optimization problems of electrical power system. Classically, it is to identify the optimal combination of generation level of all power generating units in order to minimize the total fuel cost while satisfying the loads and losses in power transmission system. In view of the sharply increasing nature of cost of fossil fuel, energy management has gained lot of significance nowadays. Herein lies the relevance of continued research on improving the solution of ELD problem. A lot of research work have been carried out on this problem using several optimization techniques including classical, linear, quadratic, and nonlinear programming methods. The objective function of the ELD problem being of highly nonlinear and non-convex nature, the classical optimization methods cannot guarantee convergence to the global optimal solution. Some soft computing techniques like *Artificial Bee Colony* (*ABC*), *Particle Swarm Optimization* (*PSO*), *Clonal Selection Algorithm* (*CSA*), *Ant Colony Optimization* (*ACO*), *Simulated Annealing* (*SA*), *Genetic Algorithm* (*GA*), etc. are now being applied to find even better solution to the ELD problem. An interesting trend in this area is application of hybrid approaches like *GA-PSO*, *ABC-PSO*, *CSA-SA,* etc. and the results are found to be highly competitive. In this book chapter, we focus on the hybrid soft computing approaches in solving ELD problem and present a concise and updated technical review of systems and approaches proposed by different research groups. To depict the differences in technique of the hybrid approaches over the basic soft computing methods, the individual methods are introduced first. While the basic working principle and case studies of each hybrid approach are described briefly, the achievements of the approaches are discussed separately. Finally, the challenges in the present problem and some of the most promising approaches are highlighted and the possible future direction of research is hinted.

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S. Bhattacharyya et al. (eds.), *Hybrid Soft Computing Approaches*,
Studies in Computational Intelligence 611,
DOI 10.1007/978-81-322-2544-7_2

Keywords Economic load dispatch · Artificial bee colony · Particle swarm optimization · Clonal selection algorithm · Ant colony optimization · Simulated annealing · Genetic algorithm · Firefly algorithm · Gravitational search algorithm

1 Introduction

The effective and economic operation and management of electrical power generating system has always been an important concern in the electrical power industry. The growing size of power grids, huge demand and crisis of energy across the world, continuous rise in price of fossil fuel necessitate the optimal combination of generation level of power generating units. The classic problem of Economic Load Dispatch (ELD) is to minimize the total cost of power generation (including fuel consumption and operational cost) from differently located power plants while satisfying the loads and losses in the power transmission system. The objective is to distribute the total load demand and total loss among the generating plants while simultaneously minimizing generation costs and satisfying the operational constraints.

The ELD problem concerns two different problems—one is the pre-dispatch problem requiring optimal selection of the generating units out of the available ones to meet the demand and produce an expected margin of operating reserve over specified time-slots. The other problem is the online dispatch in such an economic manner that the total cost of supplying the dynamic requirements of the system is minimized. Since the power generation cost in fossil fuel fired plants is very high, an optimum load dispatch saves a considerable amount of fuel and expenditure therein.

The ELD problem can be conceived as an optimization problem of minimizing the total fuel cost of all generating units while satisfying the demand and losses.

Consider a system with n power generating units. The objective function is to minimize the total fuel cost (F) given by the following expression:

$$F = \sum_{i=1}^{n} C_i(P_i) = \sum_{i=1}^{n} a_i + b_i P_i + c_i P_i^2 \tag{1}$$

Here n is the total number of generation units, a_i, b_i, c_i are the cost coefficients of ith power generation unit, P_i is the output of ith power generation unit, and C_i is the cost function of ith generating unit. $i = 1, 2 \ldots n$. The operational constraints are given by:

- *Power Balance Equation* In ELD of power, the total power generated should exactly match with the load demand and losses which is represented by the following equation. It is a kind of equality constraint.

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

Here P_i is the power output from ith generating unit, n is the number of generating units, P_L is the Transmission Loss, and P_D is the Load Demand. P_L is calculated using B-coefficient as:

$$P_L = \sum_{i=1}^{n} \sum_{j=1}^{n} P_i B_{ij} P_j \tag{3}$$

- *Generator Constraints* The output power of each generating unit is restricted by its upper (P^{max}) and lower (P^{min}) limits of actual power generation and is given by:

$$P_i^{min} \le P_i \le P_i^{max} \tag{4}$$

- *Ramp Rate Limits* In practice, the power output of a generator is not instantaneously adjustable. The operating range of all such units is restricted by their ramp rate limits during each dispatch period. So, the dispatch output of a generator should be restricted between the upper (UR_i) and down (DR_i) ramp rate constraints as expressed in Eq. (5).

$$\max\left(P_i^{min}, UR_i - P_i\right) \le P_i \le \min(P_i^{max}, P_i^o - DR_i) \tag{5}$$

Here P_i is the current power output of ith unit and P_i^o is the power generated by the ith unit at previous hour.

- *Prohibited Operating Zone* In prohibited operating zone, if any, a unit has discontinuous cost characteristics. So operation of the unit is not desirable in prohibited zones. The following constraints may be considered for such cases:

$$\begin{aligned} &P_i^{\min} \le P_i \le P_{i,1}^L (i = 1, 2, \ldots n) \\ &P_{i,j-1}^U \le P_i \le P_{i,1}^L (j = 2, 3, \ldots n_z)\ (i = 1, 2, \ldots n) \\ &P_{i,nz}^U \le P_i \le P_i^{\max} (i = 1, 2, \ldots n) \end{aligned} \tag{6}$$

Here, $P_{i,j-1}^U$ and $P_{i,1}^L$ are the upper and lower boundaries of jth prohibited zone of ith unit and n_z is the number of prohibited zones of ith unit.

Some of the other inequality constraints are *Reserve Contribution* [1, 2] and *Transmission Line Limits* [1, 2].

Thus, characteristically the ELD problem is a nonlinear and complex problem having heavy equality and inequality constraints like Ramp Rate Limits, Prohibited Operating Zone, etc. Therein lies the difficulty of the problem of finding the optimal solution. Classical methods for optimization such as Lambda Iteration [3], Newton's method [4], and Lagrange Multiplier method [5] can solve ELD problem assuming that the incremental cost curves corresponding to the generating units are monotonically increasing linear piecewise functions. However, in reality, there is distinct nonconvexity in the fuel cost function of the generating units. Classical calculus-based methods cannot address this type of problem adequately and lead to suboptimal solutions. Dynamic programming [6] can be used to solve ELD problem with cost curves discontinuous and nonlinear in nature, but it is computationally extensive and suffers from finding only local optima owing to premature convergence.

To overcome the problems of—restriction in shape of cost curves, unidirectional search, premature and slow convergence, sub-optimal solution and significant computational overhead, non-conventional stochastic and intelligent techniques are now used to resolve the complexities of ELD problem reasonably well. These techniques include *Genetic Algorithm* (*GA*) [7–16], *Particle Swarm Optimization* (*PSO*) [17–54], *Evolutionary Programming* (*EP*) [55], *Differential Evolution* (*DE*) [56–61], *Artificial Bee Colony* (*ABC*) optimization [62–64], *Ant Colony Optimization* (*ACO*) [65–69], *Artificial Immune System* (*AIS*)-*Clonal Selection Algorithm* (*CSA*) [70], *Simulated Annealing* (*SA*) [71], *Gravitational Search* (*GS*) algorithm [72], *Cuckoo Search Algorithm* (*CSA*) [73] besides others. Unlike classical optimization methods, the intelligent stochastic techniques work on a population of possible solutions in the search space and create an advantage of getting multiple suitable solutions in a single run; they are easy to implement, robust, and computationally less expensive. When applied to complex optimization problems like the ELD problem, these techniques have high probability of finding the optima quickly through competition and collaboration among the possible solutions. Basic working principles of different intelligent techniques which are used to find optimal and near optimal solution for ELD problem are briefly presented in the following sections.

1.1 Genetic Algorithm (GA)

The GA is basically an evolutionary algorithm, some of the other of its kind being evolution strategies, genetic programming, and EP. An evolutionary algorithm sustains a population of candidate solutions to an optimization problem. The population changes through repeated application of stochastic operators. Using

Tomassini's [74] terms, GA consider the ELD problem as the environment where the living individuals are the feasible solutions. Finding globally acceptable solutions to the problem is analogous to adjusting to the surrounding by a natural habitat. Just as a new generation of a population is promoted by elimination of useless traits and by developing useful features, a new and better solution is found by iterative fine-tuning of fitness function. Generally, GA enters a loop with an initial population created with a set of individuals generated randomly. In each iteration (called "generation"), a fresh population is created applying a number of stochastic operators to the earlier population (causing effect equivalent to genetic crossover and mutation).

1.2 Particle Swarm Optimization (PSO)

Particle Swarm Optimization is a population-based stochastic optimization, inspired by social behavior of bird flocking or fish schooling. In PSO, each single solution is a "bird" (particle) in the search space of food (the best solution). All particles have fitness values evaluated by the fitness function (the cost function for ELD problem), and have velocities that direct the "flying" (or evaluation) of the particles. Initialized with a set of random particles (solutions), PSO searches for the optimal solution by updating generations in each iteration. All particles are updated by two "best" values—one called the *pbest* or personal best implying the best solution or fitness a particle has achieved so far while the other one is the *gbest* or global best implying the best value obtained by any particle in the population. The best value obtained in the topological neighbour or on part of a population is a local best and is called *pbest*. Upon finding the two best values, the velocity and position of the particle are updated using following equations:

$$\begin{aligned} V_i^{t+1} &= wV_i^t + c_1\, rand_1()\left(pbest_i - X_i^t\right) + c_2\, rand_2()\left(gbest_i - X_i^t\right) \\ X_i^{t+1} &= X_i^{(t)} + V_i^{(t+1)} \end{aligned} \tag{7}$$

Here, i is the index of each particle, t is the current iteration number, $rand_1()$ and $rand_2()$ are random numbers between 0 and 1. $pbest_i$ is the best previous experience of the ith particle while $gbest_i$ is the best particle among the entire population. Constants c_1 and c_2 are the weightage factors of the stochastic acceleration terms, which pull each particle toward the $pbest_i$ and $gbest_i$, w being the inertia weight controlling the exploration properties of the algorithm. If $c_1 > c_2$, the particle tends to reach $pbest_i$, the best position identified by the particle, rather than converge to $gbest_i$ found by the population and vice versa.

PSO is very effective in finding global best of ELD problem and that is the reason why most of the hybrid techniques of solving ELD problem are found to hybridize PSO with other intelligent optimization techniques. PSO shares many similarities with GA though unlike GA, PSO has no evolution operators such as crossover and mutation. Compared to GA, the advantages of PSO are that it is easy to implement and there are few parameters to adjust. Here the particles update themselves with the internal velocity and position parameters only.

1.3 Ant Colony Optimization (ACO)

Ant Colony Optimization is another powerful swarm-based optimization technique often used to solve the ELD problem. The algorithm follows ant's movement in search of food. The ant that reaches the food in shorter path returns to the nest earlier. Other ants in the nest have high probability of following the shorter route because pheromone deposited in shorter path is more than that deposited by ants traversing longer paths.

In ACO algorithm, a number of search procedure, analogous to "ants", work parallel to find the best solutions of the ELD problem. An ant develops a solution and shares its information ("pheromone") with other ants [75]. Though each ant can build a solution, better solutions are found through this information exchange [76] within a structural neighbourhood. While developing a solution, each ant uses two information sources—one is the personal information (ant's local memory storing previously visited nodes) and the other one is an ant-decision table defined by functional combination of the publicly available (pheromone trail) and problem-specific heuristic information [77]. The publicly available information is the set of ant's decisions from the beginning of the search process. The concept of pheromone evaporation is used to prevent stagnation owing to large accumulations.

1.4 Artificial Bee Colony (ABC)

Like ACO, ABC algorithm [78] is a swarm-based metaheuristic algorithm simulating the behavior of honeybees. When applied to ELD problem, the solution produced by the algorithm is represented by the location of source of nectar while the amount of nectar represents the quality (fitness) of the solution. Employee bees fly around in search of source of nectar (representing trial in a search space) and select their preferred source of nectar based on their experience. Once search is completed, they share their findings (source) with the onlooker bees waiting in the hive. The onlooker bees then make a probabilistic selection of new source of nectar based on the information received from the employee bees. Only if the amount of nectar of the new source is higher than that of the old one, the onlookers choose the new position. If the quality of solution is not improved by a predetermined number of trials (finding sources with higher nectar), then the scout bees fly to choose new source randomly abandoning the old source. If the abandoned source is $x_{pq}, q \in$

$\{1, 2..., D\}$, where p *is* a solution and q is a randomly chosen index, then a new nectar source chosen by a bee is given by:

$$x_{pq} = x_{q\,min} + \mathrm{rand}(0,1) * (x_{q\,max} - x_{q\,min}) \tag{8}$$

Here, $x_{q\ max}$ and $x_{q\ min}$ are the maximum and minimum limits of the ELD parameter to be optimized. Each solution in the ELD solution space is a vector, D being the number of optimization parameters [79].

1.5 Firefly Algorithm (FA)

Firefly algorithm is a novel metaheuristic optimization algorithm and it has been applied successfully for ELD problem by Sudhakara et al. [80] and for Economic Emission Dispatch (EED) problem by Apostolopoulos et al. [81]. The algorithm is based on the social flashing behavior of fireflies; two important issues are the variation of light intensity (associated with the objective function) and the formulation of the attractiveness. Since a firefly's attractiveness (β) is proportional to the light intensity (I) seen by adjacent fireflies and I varies as: $I(r) = I_0 e^{-\gamma r^2}$, the attractiveness $\beta(r)$ at a distance r is determined by: $\beta(r) = \beta_0 e^{-\gamma r^2}$. The movement of a firefly i attracted to another firefly j is determined by:

$$x_{i+1} = x_i + \beta_0 e^{-\gamma r^2}\left(x_j - x_i\right) + \alpha\left(\mathrm{rand} - \frac{1}{2}\right) \tag{9}$$

Here, *rand* is a random number generator distributed uniformly in [0, 1] space and α is a randomization parameter. The third term in Eq. (9) is used to represent random movement of fireflies in case there are no brighter fireflies to attract the movement.

The FA has many similarities with other swarm intelligence-based algorithms, e.g., PSO, ACO, and ABC but from implementation point of view it is simpler than the others.

1.6 Direct Search (DS)

The Direct Search (DS) [82] optimization methods including Pattern Search (PS) algorithm, Simplex Method (SM), Powell Optimization (PO), etc. are appropriate for solving non-continuous, non-differentiable, and multimodal optimization problems such as the Economic Dispatch. The generic method is based on direct search and gradual reduction in search space. It is designed to explore a set of points, in the neighbourhood of the current position, targeting a smaller value of objective function. Since the variable's values are selected around the best position found in the previous iteration, there is better chance of convergence to the local optima. The starting point of the algorithm is a solution vector $Q(c)$ and n trial solution vectors Q_i are generated around $Q(c)$ as:

$$\begin{aligned} Q_i &= Q(c) + R(c)\ rand(-0.5, 0.5) \\ R(c) &= \psi(P_{i\,max} - P_{i\,min}) \end{aligned} \tag{10}$$

Here, $R(c)$ is the initial range vector; ψ is the multiplication factor from 0 to 1. The best solution $(Q(c) = Q_{\text{best}})$ is found which minimizes the objective function. With a reduced range vector $R(c+1) = R(c)(1-\beta)$, β being the reduction factor, the algorithm is repeated unless the best solution does not change for a pre-specified interval of generations. The main advantages of DS are the ease of framing the problem in computing language, speed in obtaining the optimum point and consistency of the results.

1.7 Biogeography-Based Optimization (BBO)

Biogeography concerns migration of species from one area to another, evolution of new species, and extinction of existing species. A habitat is any area that is geographically isolated from another area. Habitats with a high habitat suitability index (*HSI*) tend to have a large number of species, while those with low *HSI* have a small number of species. Habitats with a high *HSI* have a low immigration rate and a high emigration rate of species because they are overpopulated. On the contrary, habitats with a low *HSI* have a high immigration rate and low emigration rate because of their sparse population of species. Following this natural phenomena, in the ELD optimization scenario, the best solution is assumed to have the best possible features. As higher *HSI* implies lesser chance of sharing its features, a solution having better feature also has greater probability of sharing those features. This Biogeography-based Optimization (BBO) approach has yielded fairly good solution values for ELD problem [83].

1.8 Gravitational Search Algorithm (GSA)

The basis of Gravitational Search Algorithm (GSA) [84] is the law of gravity. In GSA, performances of the objects (agents) are measured with a fitness function which is expressed in terms of the masses of the objects. Assuming a system with n masses X_i (i = 1, 2, 3, … ,n), the force acting on ith mass (M_i) from jth mass (M_j), at a given iteration (k), is defined as follows:

$$F_{ij}^{d}(k) = G(t)\frac{M_{pi}(k) \times M_{aj}(k)}{R_{ij}(k) + \varepsilon}\left(X_{j}^{d}(k) - X_{i}^{d}(k)\right) \tag{11}$$

Here $G(k)$ is the gravitational constant, ε is a small constant, and $R_{ij}(k)$ is the Euclidian distance between ith and jth agents. New positions imply new masses. In each iteration, the masses (m and M) and acceleration (a) are updated by the following equations:

$$m_i(k) = \frac{fit_i(k) - worst(k)}{best(k) - worst(k)};\ M_i(k) = \frac{m_i(k)}{\sum_{j=1}^{N} m_j(k)};\ a_i^d(k) = \frac{F_i^d(k)}{M_i(k)} \tag{12}$$

Here $fit_i(k)$ represents the fitness value of the ith agent at iteration k. For a minimization problem like ELD, the worst and best values at iteration k, i.e., $worst(k)$ and $best(k)$, respectively, are defined as follows:

$$best(k) = min\{fit_i(k)\};\ worst(k) = max\{fit_i(k)\} \tag{13}$$

1.9 Clonal Selection Algorithm (CSA)

The Artificial Immune System (AIS) is a powerful computational intelligence method based on the natural immune system of human body. CSA is a class of AIS algorithm inspired by the clonal selection theory of response to infections by the immune system. In CSA, a candidate solution is called an antigen—an agent that invades the body, which is recognized by the antibody—the defense agent that destroys antigen. An antibody represents a possible improved solution to the problem. CSA when applied to find optimal solution of ELD [70], first an initial population of N antibodies is randomly produced in the problem space and the affinity of each antibody is determined (by evaluating objective function). Then antibodies which have the highest affinity are selected and copied to generate an improved new population of antibodies as per Eq. (14). Higher the affinity of an antibody, more copies will be generated.

$$nc = round\left(\frac{\beta.N}{i}\right), \quad i = 1, \ldots, n \tag{14}$$

where nc is the number of copies of antibodies from ith antibody (parent) and β is a constant which indicates the rate of copy. Finally, the number of antibodies (Nc) in the regenerated population would be

$$Nc = round\sum_{i=1}^{n}\left(\frac{\beta.N}{i}\right) \tag{15}$$

Nc antibodies are mutated in proportion to their affinities and after determining the affinity of each mutated antibodies, *m* antibodies with higher affinity are selected which enter the next generation directly. *p* new antibodies are generated randomly and increase the population. These new antibodies add to the diversity of the solution and subsequent convergence to local optima is avoided. This cycle is repeated until the termination criterion is met.

1.10 Simulated Annealing (SA)

Simulated Annealing [71] is a powerful algorithm for many optimization problems and it has been successfully applied for ELD problem as well. The idea behind this algorithm is the annealing process of metals. In this process a metal is heated up to a high temperature and then cooled down step-by-step till the metal reaches its lowest energy state. At each step of cooling, the temperature is fixed for a certain period of time allowing thermal equilibrium of the system. In SA, the objective function corresponds to the energy state of the metal and iterations emulate the temperature levels in the annealing process. When SA is applied in an ELD problem, it starts from a random point (starting temperature) and during processing new points (temperature levels) are generated resulting in convergence to the global optima.

The objective function determines the strength of every new point and calculates the change in energy (ΔF). If $\Delta F < 0$, the new point replaces the old point. Else (i.e., if $\Delta F \geq 0$) the new point is retained with some probability (following Boltzmann probability distribution). The efficiency of SA in solving ELD mostly depends on selection of starting point. Linear or exponential decrement of temperature (in each iteration) reduces the probability of acceptance of the worse point which in turn helps avoiding local minima.

1.11 Differential Evolution (DE)

Differential Evolution is a population-based stochastic parallel search technique (similar to GA) that has been proved to be effective for solving ELD problems [56–61]. DE starts with an initial population of feasible solutions (parents) and generates new solutions (child) using three genetic operators—mutation, crossover, and selection until the optimal solution is reached. The mutation operation involves three solution vectors ($X_{ra}^G, X_{rb}^G,$ and X_{rc}^G), which are randomly selected from a population of N_P solution vectors. A mutant vector (V_i^{G+1}) is created by combining one vector with the difference of two other vectors as per following equation:

$$V_i^{G+1} = X_{ra}^G + F\left[X_{rb}^G - X_{rc}^G\right],\ i = 1, 2..., N_P \tag{16}$$

where F is the scaling factor and $ra \neq rb \neq rc \neq i$.

In the crossover operation, certain parameter(s) of the targeted vector is replaced by the corresponding parameter of the mutant vector based on a probability distribution to create a new trial vector (child). Thus, the crossover operator efficiently extracts information from successful combinations thereby triggering search in a better solution space. DE also uses nonuniform crossover where child vector is often taken from only one parent. So the parent competes with the child. The fittest individual survives until the next generation.

1.12 Bacteria Foraging (BF)

Bacteria Foraging is a swarm optimization method that provides certain advantages in handling complex dynamic ED problem in area of power system optimization [85]. Chemotaxis is a foraging behavior whereby a bacterium tries to reach toward more nutrient concentration. If θ be the initial position of bacterium then $J(\theta) < 0$, $= 0$, and > 0 represent nutrient rich, neutral, and noxious environment of the bacteria, respectively. By chemotaxis, lower values of $J(\theta)$ are searched and positions corresponding to $J(\theta) \geq 0$ are avoided. In the context of ELD problem, the objective function (cost function) represented by $J(\theta)$ is calculated at each chemotactic step j, the step size being $C(i)$. If at position $\theta(j + 1)$, the value J is greater than that at position $\theta(j)$, the process will be repeated for the subsequent steps (subject to a maximum N_s number of steps) until a minimum value of J is reached. After N_c chemotactic steps, a reproduction step (N_{re}) is taken in which the population is stored in ascending order of J value. The least healthy bacteria are thereby replaced by copies of the healthiest bacteria. This is followed by the process wherein each bacterium in the population undergoes elimination (dispersal to a random location) with probability p_{ed} [86].

2 Hybrid Approaches for Solving ELD Problem

Though different soft computing methods like those discussed above were applied in solving ELD problem to overcome the limitations of the classical optimization methods, they too have their own limitations. This includes stagnation of fitness function at a local best value for a long time, dead loop of idle individual, loss of fitness quality with iteration, and slow exploration of search space. To further eliminate these limitations and to improve the quality of solutions, various hybrid approaches have evolved by combining the individual soft computing techniques in pairs. Fifteen such selected (including one new) hybrid methods are presented in this section to represent the state-of-the-art in hybrid soft computing application in ELD problem. The hybrid combinations are found to generate high quality solution with sure, fast, and stable convergence, modeling flexibility and robustness, greater consistency, and less computational time compared to the individual soft computing techniques.

Most hybrid methods, found in the literature, for solving ELD problems use PSO technique in combination with other soft computing techniques described in Sect. 1. Hence, approaches that use PSO as a common hybrid component are discussed first followed by other hybrid approaches not using PSO.

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

Application of hybrid PSO-DS technique in solving ELD problem was done by Victoire and Jeyakumar [87]. The steps of the method are given below.

Step 1 Input data
Step 2 Random initialization of search points and velocities of PSO agents
Step 3 Do while (Termination criterion not met)
Step 4 Evaluate the objective function and update the weights
Step 5 Modify the searching points and velocities
Step 6 If solution improves, then
Step 7 Fine-tune the search region using DS
Step 8 End while

Different test cases of Economic Dispatch (ED) problem (based on fuel cost functions) were studied by Victoire et al. [87] to illustrate the flexibility and effectiveness of the PSO-DS approach using MATLAB 6.1.

Case 1 This test was done with 13 generating units. To simulate the valve-point loading effects of generating units, a sinusoid component is added to the quadratic fuel cost function (Eq. 17) thereby making the model more realistic. This also increases the non-linearity and number of potential local optima in the solution space.

$$F_i(P_i) = a_i P_i^2 + b_i P_i + c_i + |e_i(\sin(f_i(P_{i\,min} - P_i))| \tag{17}$$

Here e_i and f_i are cost coefficient of the ith generating unit.

A comparison of PSO-DS performance (with GA, SA, and hybrid GA-SA methods) for a load demand of 2520 MW is shown in Table 1. The overall result of PSO-DS method is found to be better than the other three methods. [87] can be referred for detailed data for this test system.

Case 2 This test was done with 3 subsystems and 10 generating units with multiple-fuel options. Unlike conventional ED problem which has a quadratic cost function, this system has piecewise quadratic fuel cost function (Eq. 18) as multiple fuels are used for generation.

Table 1 Comparison of results for Case 1 (13 units, 2520 MW load)

Generator	Cost per unit generation (MW)			
	GA	SA	GA-SA	PSO-DS
z1	628.32	668.40	628.23	628.3094
z2	356.49	359.78	299.22	298.9996
z3	359.43	358.20	299.17	298.8181
a1	159.73	104.28	159.12	159.7441
a2	109.86	60.36	159.95	159.5509
a3	159.73	110.64	158.85	159.1718
a4	159.63	162.12	157.26	159.5712
b1	159.73	163.03	159.93	159.5940
b2	159.73	161.52	159.86	159.4003
b3	77.31	117.09	110.78	113.6156
c1	75.00	75.00	75.00	113.2250
c2	60.00	60.00	60.00	55.0000
c3	55.00	119.58	92.62	55.0000
Total cost ($/h)	24398.23	24970.91	24275.71	24182.55

$$F_i(P_i) = \begin{cases} a_{i1} + b_{i1}P_i + c_{i1}P_i^2, & P_{i\,min} \le P_i \le P_1 \\ a_{i2} + b_{i2}P_i + c_{i2}P_i^2, & P_1 \le P_i \le P_2 \\ a_{i3} + b_{i3}P_i + c_{i3}P_i^2, & P_2 \le P_i \le P_{i\,max} \end{cases}. \quad (18)$$

Here, a_{ij}, b_{ij}, c_{ij} are cost coefficients of the ith generating unit for fuel type j, (j = 1, 2, 3).

The generating units were expected to supply load demands of 2400 MW, 2500 MW, 2600 MW, and 2700 MW, [88] can be referred for detailed data for this system. In Table 2, the performance of the PSO-DS method for Case 2 is compared with those of Numerical Method (NM), Enhanced Lagrangian Neural Network (ELNN) method [88], GA [89], and EP [90].

The authors observed that PSO gets stagnated after the 15th iteration and generated a solution which is local optimum. Whereas PSO-DS further explores to find much optimized solution than the one generated by PSO. Also, the PSO-DS is applied in Case 2 experiment with various agents and the experiment proved that, the number of agents above 200 does not have considerable influence on the convergence characteristics and quality of solution.

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

An application of hybrid chaotic PSO-IF method in ELD problem was examined by Coelho and Mariani in the year 2007 [91]. IF is an applied Quasi-Newton direct

Table 2 Comparison of results for Case 2 (10 units, varying load)

P_D (MW)	Fuel cost (\$/h)				
	NM	ELNN	GA	EP	PSO-DS
2400	488.50	481.74	482.00	481.79	481.72
2500	526.70	526.27	526.24	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

search method; it is a generalization of the gradient projection algorithm [92] that calculates derivatives with difference quotients. The step sizes in the difference quotients are iteratively changed to avoid local minima attributed to high-frequency, low-amplitude oscillations. Chaotic PSO is different from traditional PSO in the sense instead of random processing, chaotic mapping is done with the stochastic properties of PSO to improve convergence to the global optima. In chaotic motion every possible state in a search space is visited only once thereby having no specific periodicity.

The PSO-IF approach proposed in [91] is based on Hénon map [93] which is a simplified version of the Poincaré map of the Lorenz system [93]. The Hénon equations are as follows:

$$\begin{aligned} y(t) &= 1 - a\{y(t-1) + z(t-1)\} \\ z(t) &= b\{y(t-1)\} \end{aligned} \tag{19}$$

$$\begin{aligned} V_i^{t+1} = {} & wV_i^t + c_1\, rand_1()\left(pbest_i - X_i^t\right) + c_2\, rand_2()\left(gbest - X_i^t\right) \\ & + (c_1 + c_2)Z_{i,j}(t)d_j[P_j - x_i^t] \end{aligned}$$

Here $Z_{i,j}(t)$ values between 0 and 1 are found from Hénon map; P_j is the mean value of previous best positions of the jth dimension; and d_j is a distance factor of the jth dimension based on historical knowledge sources [94]. d_j is calculated as follows:

$$d_j = sgn\left(\sum_{i=0}^{n} sgn(v_i(t))\right) \tag{20}$$

where the function *sgn(x)* returns the sign of x.

The authors Coelho and Mariani [91] presented a report on three case studies involving 13 thermal units of generation with the effects of valve-point loading; one of the case studies is given in Table 3. In the test cases the load demand (P_D) was 1800 MW. The result establishes the supremacy of the hybrid PSOs (particularly Chaotic PSO-IF) over PSO, Chaotic PSO, and IF.

Table 3 Convergence results for 50 runs (13 units, 1800 MW load)

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	14.8	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)

In 2010, Pandian and Thanushkodi [95] proposed a new hybrid method combining EP and Efficient Particle Swarm Optimization (EPSO) techniques to solve ELD problems with transmission losses. In the EP sub-problem, after random initialization of population (of solutions), a new population is generated by adding a Gaussian random number with zero mean and fixed standard deviation. Then a stochastic tournament method is used for selection. The proposed method extends the basic PSO by modifying the formulation for updating the position, velocity, *pbest*, and *gbest* while satisfying the constraints in a different way.

The effectiveness of the proposed hybrid method in solving ELD problem is tested on the data of a 40-unit system; two ELD problems are considered—one with smooth and another with non-smooth cost functions, the later considering valve-point loading effects. Simulation in MATLAB shows that the EP-EPSO method yields a lower production cost compared to the cost for Neural Network (NN), EP, EPSO, and hybrid NN-EPSO as shown in Table 4.

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

A hybrid GA-PSO method was proposed by Younes and Benhamida in the year 2011 [96]. In this approach both algorithms are executed simultaneously. After N iterations, values of P individuals selected by each algorithm are interchanged.

Table 4 Comparison of results (40 units)

Optimization 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

The individual with larger fitness is finally selected. The steps of the hybrid approach are as follows:

Step 1 Initialize GA and PSO

Step 2 Run GA and PSO simultaneously

Step 3 Stop once the best individual in any process satisfies the termination criterion. Remember the best solution

Step 4 Select *P* individuals from both processes according to their fitness and exchange values. Go to step 3.

The GA-PSO approach has been tested with five demand load situations for IEEE 25-bus system and the results have been compared with those obtained for classical optimization methods such as Broyden–Fletcher–Goldfarb–Shanno (BFGS) and intelligent methods such as Binary-Coded Genetic Algorithm (BCGA) [97], Real-Coded Genetic Algorithms (RCGA) [98], and PSO separately. Table 5 depicts the comparative where GA-PSO approach shows the most economic value.

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

In 2012, Soni and Pandit [99] proposed two hybrid approaches based on PSO—one is Self-Organizing Hierarchical PSO or SOH-PSO and the other is Fuzzy Adaptive PSO or FA-PSO. The FA-PSO being more useful (of the two) with respect to ELD, is briefly described here.

Observing the long-time stagnation (at one fitness value) often caused by PSO, fuzzy technique is introduced in PSO. The output variables, i.e., the inertia weight (w) and learning factors (c_1 and c_2) are adjusted with input variables—the best unchanged fitness (NU) and the number of generations. The best fitness (BF) represents the best candidate solution. The ELD problem has different ranges of the best fitness values which are normalized into [0, 1] using the following formula:

$$NBF = \frac{BF - BF_{min}}{BF_{max} - BF_{min}} \tag{21}$$

Table 5 Comparison of results (IEEE 25-bus system, constant loss 414,487 MW)

P_D (MW)	BFGS	BCGAs	RCGAs	PSO	GA-PSO
P1	211.30	206.72	213.68	197.45	211.54
P2	126.30	121.64	127.46	114.93	122.46
P3	151.29	151.82	141.93	168.29	140.117
P4	71.24	33.21	29.53	29.08	27.358
P5	211.31	358.05	258.86	259.29	267.514
Total cost ($/h)	2029.3	2011.0	2010.8	2099.00	2007.44

Here, BF_{max} and BF_{min} are the maximum and minimum BF values, respectively. NU values are normalized in a similar way. The bound values for w, c_1, and c_2 are: $0.2 \le w \le 1.2$, $1 \le c_1$ and $c_2 \le 2$. Following are the steps of the FA–PSO algorithm for solving ELD problem:

Step 1 Randomly generate initial population and velocity of each particle
Step 2 Evaluate the objective function for each particle
Step 3 Select global best position for the ith particle having least value of objective function
Step 4 Select best local position for the ith particle
Step 5 Update the population and velocity parameters
Step 6 Find the next position for each particle based on the updated parameters and Eq. (21)
Step 7 If all particles are selected, Go to Step 8,
Else $i = i + 1$
Go to Step 4
Step 8 Stop search if number of iteration reaches terminal value,
Else go to Step 2

The method has been tested with a system of 6 generators, 46 transmission lines, and 26 buses for a demand of 1263 MW and a comparison of performance of FA-PSO with SOH-PSO and traditional PSO is shown in Table 6.

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

Manteaw and Odero [100] proposed in 2012 a hybrid optimization approach for solving combined ELD and ED (Emission Dispatch) problem involving ABC algorithm and PSO technique. The objectives are combined using weighting function and the best combined objectives are determined by cardinal priority ranking method through normalized weights.

In this hybridization, ABC executes till the terminal criterion is reached. After this, the best values of individuals generated by the ABC are given as input to the PSO. Generally, the PSO randomly generates its first individual sets but in this hybridized approach, the output of ABC is the input of PSO. The logical steps of the ABC-PSO approach are:

Table 6 Comparison of results (6 units, load 1263 MW)

Method	Best cost ($)	Worst cost ($)	Average cost ($)
FA–PSO	15,445.24	15,451.60	15,448.05
SOH–PSO	15,446.00	15,451.7	15,450.3
Simple PSO	15,466.61	15,451.7	15,450.3

Step 1 Execute ABC
Step 2 Generate best values for all individuals
Step 3 Take these values as input to PSO
Step 4 Execute PSO until stopping criterion is reached.

The authors have reported testing of the ABC-PSO method in a 10-generator system with 2000 MW demand load simulated in MATLAB 2009. Comparison (of performance) with some other methods such as DE, Non-Sorting Genetic Algorithm (NSGA), and Strength Pareto Evolutionary Algorithm (SPEA) is shown in Table 7.

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

Very recently, Dubey et al. [103] have proposed a hybrid PSO-GSA method to solve ELD problem.

The main idea of PSO-GSA is to combine the social behavior (*gbest*) in PSO with the localized search capability of GSA. In PSO-GSA, all agents are randomly initialized first. After initialization, the force $F_{ij}^{d}(k)$ acting on agent i, mass $M_i(k)$ and acceleration $a_i^d(k)$ of agent i are calculated using Eqs. (11) and (12) of Sect. 1.8. The best solution (fitness for each agent) should be updated after each iteration. The velocities of all agents are then updated using the following modified PSO expression (refer Eq. (7) in Sect. 1.2):

$$V_i^{k+1} = wV_i^k + c_1\, rand_1\, a_i^d(k) + c_2\, rand_2 \left(gbest_i - X_i^k\right) \tag{22}$$

The agent positions are also updated following Eq. (7) and the process is repeated until the stopping criterion is met.

In one of the four case studies done by the authors, a 6-unit generator system with 1263 MW total demand has been used to validate the effectiveness of the PSO-GSA method in optimizing ED considering non-equality constraints like ramp rate limits and generator prohibited zones. The algorithm is implemented in MATLAB 7.8. A performance comparison with nine other optimization methods is depicted in Table 8.

The same hybridization approach involving PSO and GSA has been used by Ashouri and Hosseini in year 2013 [102]. In this approach a more effective method has been used in PSO for the movement of particles, considering the worst solutions of every individual and also the global solution. One notable change is in the

Table 7 Comparison of results (10 units, load 2000 MW)

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

formulation of updating velocity of agents as given by Eq. (23). The weight factors (ω) have been modified too.

$$V_i^{k+1} = \omega V_i^k + c_1\, rand_1 a_i^d(k) + c_2\, rand_2\left(gbest_i - X_i^k\right) + c_3\, rand_3\left(X_i^k - P_{\text{worst}}^k\right) \tag{23}$$

The result of the experiment and comparison done (with a 6-generator system) with hybrid GA and a special class Ant Colony Optimization (GA-API), Tabu Search Algorithm (TSA), GA, SA, DE, Intelligent PSO (IPSO), and traditional PSO is tabulated in Table 9.

In the following sub-sections some hybrid methods are discussed that involve intelligent techniques other than PSO. The comparative (results) with other methods are also shown in each case.

2.8 Simulated Annealing—Clonal Selection Algorithm (SA-CSA)

In 2010, Amjadi and Sharifzadeh [104] developed a new hybrid approach for power generation optimization. In this approach, the hybridization of SA and CSA is accomplished in the selection step of CSA. The selection of population is done at two levels: first using CSA and then using SA.

When the usual method of CSA is applied, the degree of affinity causes selection of antibodies from the whole population. At the next level, antibodies selected from the previous level and the initial population is compared. In the next iteration selection is based on SA following the criteria given in Eq. (24):

Table 8 Comparison of results (6 units, load 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

NPSO-LRS New Particle Swarm with Local Random Search, *ABF-NM* Adaptive Bacteria Foraging with Nelder–Mead Technique [101], *HS* Harmonic Search

Table 9 Comparison of results (6 units, load 1263 MW)

Methods	P_{loss} (MW)	Total cost (\$/h)
PSO-GSA	12.72	15444.00
IPSO	12.55	15444.10
GA-API	12.98	15449.70
DE	12.96	15449.70
GA	13.02	15459.00
PSO	12.95	15450.00
TSA	14.34	15451.63
SA	13.13	15461.10

$$P(t+1) = \begin{cases} P_i'(t), F\left(P_i'(t)\right) < F(P_i(t)) \\ P_i'(t), F\left(P_i'(t)\right) > F(P_i(t)) h(P_i(t), P_i'(t) > rand \\ P_i(t), \text{ otherwise} \end{cases} \tag{24}$$

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

$$T(iter+1) = \alpha T(iter) \,\text{and}\, T(0) = T_0$$

In the above equation, normalized difference between the parent and offspring objective functions $\left[\frac{F(P_i(t)) - F(P_i'(t))}{F(P_i(t))}\right]$ has been considered to eliminate the effect of diversity of objective functions.

A case study done with 10-unit system and load of 2700 MW shows applicability of the method in minimizing the fuel cost function of ELD problem. A comparison of performance of SA-CSA method has been done with some contemporary methods as shown in Table 10.

2.9 *Bacterial Foraging-Differential Evolution (BF-DE)*

Biswas et al. [105] reported a hybrid approach combining BF and DE algorithms in 2009. The resulting algorithm is also referred as the CDE (Chemotactic Differential Evolution).

The authors have incorporated into DE an adapted form of chemotactic step that characterizes BF. BF is a stochastic application of computational chemotaxis that makes local search based on gradient descent method. One disadvantage of DE is that the global optima may not be approached till the population converges to a local optima or any other point. Moreover, new individuals may add to the population but DE gets stagnated and does not proceed toward a better solution [106]. In this hybrid approach, the convergence characteristics of the classical DE have

Table 10 Comparison of results (10 units, load 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	628.3214
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

been improved by introducing foraging random walk vector. BF successfully breaks the dead loop of an idle individual and helps to jump from the local minima quickly.

The authors have tested their method with a 6-unit system (with a demand load of 1263 MW) and the comparative result with respect to other conventional and hybrid approaches is tabulated in Table 11.

2.10 Genetic Algorithm—Active Power Optimization (GA-APO)

Malik et al. [107] presented a new hybrid approach involving GA and Active Power Optimization (APO) and have reported its use for the solution of ELD problem with valve-point effect. The proposed approach is able to fine-tune the near optimal results produced by GA.

APO is based on Newton's second-order approach (NSOA). APO is developed and implemented by the authors using some technique of storage optimization and classical linear system solution method. In the proposed hybrid approach, GA works as a global optimizer and produces near optimal generation schedule. APO works on this schedule and replaces the power output at the generation buses. It dispatches the active power of the generating units to minimize the cost and produce optimum generation schedule.

GA-APO is implemented in a computational framework called PED Frame [108] in visual C environment. One can input cost curves and other ELD-specific information through PED Frame and can also get output in standard format.

Table 11 Comparison of results (6 units, load 1263 MW)

	BF-DE	PSO	GA	NPSO-LRS	CPSO1
Minimum cost	15444.1564	15,450	15,459	1540	15,447

Table 12 Different IEEE systems results comparison

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

The authors have investigated three test systems to demonstrate the effectiveness of their hybrid approach. The test systems consists 3-machines 6-bus system [109], IEEE 5-machines 14-bus system [110], and IEEE 6-machines 30-bus system [111]. The outputs are compared in Table 12. The coefficients e_i and f_i reflecting valve-point effects are introduced in the system to convert the quadratic convex cost curve into nonconvex cost curves.

2.11 Differential Evolution—Biogeography-Based Optimization (DE-BBO)

In 2010, Bhattacharya and Chattopadhyay [112] presented application of hybrid DE-BBO method in ELD problem taking into account transmission losses, and constraints such as ramp rate limits, valve-point loading, and prohibited operating zones.

Though DE yields optimum ELD solution satisfying all the constraints, one of its major disadvantages is that DE is unable to map its entire unknown variables together efficiently when the system complexity and size increase. Owing to the crossover operation in DE, solutions having good initial fitness value often suffer loss of quality during further processing. BBO has got no crossover stage and solutions gradually mature as the algorithm proceeds through migration operation. The most striking characteristic of DE-BBO is hybridization of migration operation. In this algorithm, new features are developed in child population from corresponding parents through mutation (caused by DE) and migration (caused by BBO). Here, good solutions would be less destroyed, while poor solutions can take a lot of new features from good solutions.

The performance of hybrid approach (developed in MATLAB 7) has been compared for a system of 10 generating units with few other hybrid approaches like NPSO-LRS, PSO-LRS, IGA-MU, and CGA-MU. The result is presented in Table 13.

Table 13 Comparison of results (10 units)

Methods	Generation cost ($/h)		
	Max.	Min.	Average
DE-BBO	605.62	605.62	605.63
NPSO-LRS [113]	626.99	624.13	624.99
PSO-LRS [113]	628.32	624.23	625.79
IGA-MU [114]	630.87	624.52	625.87
CGA-MU [114]	633.87	624.72	627.61

2.12 *Hybrid Immune Genetic Algorithm (HIGA)*

Hosseini et al. [115], in the year 2012 proposed application of Hybrid Immune Genetic Algorithm (HIGA) in solving ELD problem. This is a hybridization of Immune Algorithm and GA.

The Immune Algorithm creates an initial solution set and iteratively improves its performance using affinity factor, hyper-mutation operator, and clonal selection [116]. The affinity factor ($AF = (TC_n)^{-1}$) is a measure of strength of solutions in optimizing the antigens (objective functions). The hypermutation operator acts like the mutation operator in GA [117], but unlike in GA, the probability of mutation in Immune Algorithm is inversely proportional to the affinity factor of the solution. Thus, if the affinity factor (of a solution) is low, it will be more mutated to be able to explore the solution space and vice versa. In clonal selection, the crossover operator is used to propagate the attributes of high-quality solutions among others. This sometimes causes reproduction of each solution depending on affinity factor of the solution.

The cost comparisons of HIGA optimization on 6-unit and 40-unit power generation systems are presented in Tables 14 and 15, respectively.

2.13 *Fuzzified Artificial Bee Colony Algorithm (FABC)*

A recent study has been done by Koodalsamy and Simon [118] to demonstrate the efficiency of a hybrid Fuzzy Artificial Bee Colony (FABC) algorithm for solving multi-objective ED problem, i.e., minimizing (i) probability of energy unavailability,[1] (ii) emission cost, and (iii) fuel cost simultaneously while satisfying load demands and operational constraints. In this approach, ABC works with a fixed number of bees that fly around in a multidimensional search space to locate the food sources. With every generation cycle of ABC, the best compromise is chosen from

[1]This is equivalent to Expected Energy Not Supplied (EENS); higher the EENS, lower is the reliability level.

Table 14 Comparison of results (6 units, load 1263 MW)

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

Table 15 Comparison of results (40 units, load 10,500 MW)

	DE-BBO	BBO	QPSO	HIGA
Total cost	121420.90	121426.95	121448.21	121416.94

the Pareto optimal set using fuzzy fitness. The normalized membership function for fuzzy fitness is calculated as:

$$FIT_p = \frac{(\mu_c^p + \mu_e^p + \mu_r^p)}{\sum_{p=1}^{m} (\mu_c^p + \mu_e^p + \mu_r^p)} \tag{25}$$

$$\mu_j^p = \begin{cases} 1, & for\, F_i \leq F_{i\,min} \\ \frac{(F_{j\,max} - F_j)}{(F_{j\,max} - F_{j\,min})}, & for\, F_{j\,min} < F_j < F_{j\,max} \\ 0, & for\, F_j \geq F_{j\,max} \end{cases} \tag{26}$$

Here m is the total number of non-dominated solutions or population of bees and p is the pth position of bees or food sources. The fuzzy membership functions μ_c^p, μ_e^p and μ_r^p are related to cost, emission, and reliability objective functions, respectively. The design of μ_c^p, μ_e^p and μ_r^p, i.e., μ_j^p is shown in Eq. (26) where F_j is the degree of the objective function in the fuzzy domain. The best compromise solution corresponds to the maximum value in the population implying food sources with highest quality of nectar information.

The authors have tested the algorithm using MATLAB 7. Out of several test cases carried out to validate the FABC algorithm, the results of solving EED problem of IEEE 30-bus system for two different load conditions (2.834 MW and 2.8339 MW) and comparisons with other reported methods are shown in Table 16.

2.14 Firefly Algorithm-Ant Colony Optimization (FFA-ACO)

Younes [119] proposed the hybrid approach involving FFA and ACO algorithm in 2013.

According to this algorithm, first an initial population n of fireflies x_i is generated. Light intensity of firefly is determined by the objective function. New solutions or attractiveness of fireflies are evaluated and light intensity updated as firefly i is moved towards j. The fireflies are ranked according to attractiveness and the

Table 16 Comparison of results (6 units, IEEE 30 bus system)

Load	2.834 MW		2.8339 MW			
Method	MOPSO	FABC	NSGA	MOHS	MBFA	FABC
Total cost ($/h)	938.91	938.75	938.46	939.92	938.33	938.24

best (solutions) are passed as initial points of ACO. Following the scheduled activities in ACO, the ant's response functions are compared and communication with best ant response is made to get the best solution.

The FFA-ACO approach has been developed using MATLAB 7. It is tested using the modified IEEE 30-bus system consisting of 6 generators (with power demand of 283.40 MW). A comparison of performance of FFA-ACO has been done with few other approaches (refer Table 17).

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

In the previous subsections, we have discussed some hybrid methods that are used to get optimized solution of ELD problem. The studies conducted by the researchers confirm that the PSO method itself can be used as an effective and powerful technique for optimizing ELD solution. However, one of its prominent weaknesses found is that it may get stuck into local optima if the global best and local best positions become identical to the particle's position repeatedly. To alleviate this drawback, hybrid methods combining PSO with other global optimization algorithms like GA, IF, EP, FA, ABC, GSA have been used. Now, in addition to these, a new hybrid of PSO is suggested by the present authors by combining PSO with ACO to study whether better optimization of ELD solution can be achieved. To the best of our knowledge, study of ELD problem solving using PSO-ACO hybrid approach has not been reported in the literature. In this approach, new generation members can be produced at each iteration using PSO and then ACO algorithm can be applied to create extended opportunity of fine-tuning the members.

In PSO algorithm, if the *gbest* value does not change over few iterations, other particles are drawn closer to the *gbest* position. As the velocity of the *gbest* particle gradually reduces by iteration, exploring the local search space (by the best agent) also diminishes. Here the ACO algorithm comes into play. Taking the *gbest*

Table 17 Comparison of results (6 units, load 283.40 MW)

	MDE-OPF [120]	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

particles as the input, following the schedule activities of ACO, the ant's response functions are compared and communication with best ant response is made to eventually get the best solution.

The suggested steps of the PSO-ACO method are given below.

Read the input data
Initialize the search points and velocities in PSO
While (Termination criterion not met)
    Evaluate the objective function for each individual and update the inertia weight
    Modify the searching points and velocities
    If solution improves, then
        Store the solution for ACO
    End if
End while
The best solutions found by PSO are passed as starting points for ACO
While (termination criterion not met)
    Generate path for each ant
    Compare response function
    If value of response function not better than earlier **then**
        Exchange with best ant's response function
        Generate path from local position to best ant
    Else
        If value of response function is better **then**
            Repeat while loop
        Else
            Wait for exchange with best ant
        End if
    End if
End while

3 Discussion

The observations that can be made regarding the performance of the PSO-DS method proposed by Victoire and Jeyakumar [87] are: the reliability of producing quality solutions, searching efficiency as iteration proceeds, accuracy of the final solution and convergence characteristics when the numbers of agents are varied. The PSO is very fast compared to other evolutionary techniques, but it does not possess the ability to improve upon the quality of the solutions as the number of generations increases. When the solution of the PSO improves in a run, the region will be fine-tuned with the DS method.

The performance of the PSO-DS method was tested with two EDP test cases and compared with the results reported in the literature for few other methods. Test result shows that the PSO-DS method is capable of handling load demand at various time intervals with no restrictions on the cost function of the units. As claimed by the authors, 77 % of the 100 trial runs produced quality solution and the convergence characteristic resembles the same for all the 100 trial runs which indicates the reliability and robustness of PSO-DS method. This hybrid method is scalable for solving the DEDP with more inequality constraints such as prohibited operating zones and spinning reserves. More accurate dispatch results can then be achieved in actual power situations.

The contribution of Coelho and Mariani [91] is the hybridization of the PSO (using Hénon map) and the Implicit Filtering (IF) direct search to solve an EDP. Chaotic PSO approach is good in solving optimization problem but often the solutions are close to but not exactly the global optimum. To get rid of this limitation, the hybrid PSO-IF approach seems to be a promising alternative.

The combination of chaotic PSO with IF is a kind of sequential hybridization directed for local search. Function of chaotic PSO is global search within a population, while function of IF is exploitation around local best solution produced by chaotic PSO in each iteration. IF explores the local search space quickly, jumps over local minima, and implicitly filters the noise.

The PSO-IF hybrid method is validated on a test bed emulating 13 thermal units. The fuel cost function considers the valve-point loading effects. The simulation result reported by the authors is comparatively better than some of the recent studies reported in the literature. The complementary search ability of chaotic PSO-IF renders its usefulness to multi-constrained optimization problems in planning and operation of power system.

In the study done by Pandian and Thanushkodi [95], a new methodology involving EP combined with EPSO has been proposed for solving non-smooth ED problem with valve-point loading. There are two parts in the proposed algorithm. The first part exploits the ability of EP in generating a near global solution. When EP meets the terminal criteria, the local search capability of EPSO is exploited to adjust the control variables so as to achieve the final optimal solution. In effect, faster convergence is obtained when EP is applied along with EPSO.

The mean cost value obtained by EP-EPSO in the ED simulation is less compared to other methods studied. Thus EP-EPSO has been established by the authors as a powerful tool for optimizing feasible solutions of the non-convex ELD problem.

The approach of PSO is similar to GA considering the fact that their search processes using probabilistic rules are based on exchange of information among the members of population. The objective of the research by Younes and Benhamida [96] is to combine PSO and GA to improve the effectiveness of the search process as a whole. The feasibility of the hybrid algorithm is tested successfully on an IEEE

25-bus system. The results show that the GA-PSO approach is quite effective in handling nonlinear ELD problems.

Long processing time and uncertainty of convergence to the global optima are the main disadvantages of GA. Again unlike GA, PSO can quickly find a good local solution but get stuck to it for rest of the iteration. The GA-PSO hybrid combination can generate a much better solution with stable convergence and appears superior over many other hybrid approaches in terms of flexibility of modeling, reliable and speedy convergence, and less processing time.

In [99], a new hybrid optimization algorithm, called FA-PSO, was presented by Soni and Pandit for solving non-convex ED problem (considering prohibited operating zones and ramp rate constraints) in power system. In FA-PSO, acceleration factors are co-evolved with the particles and the inertia weight is adjusted through fuzzy mechanism. To avoid stagnation around local optima and explore the search space effectively, this method uses a new mutation operator.

Two case studies have been employed (with systems consisting of 6 and 15 thermal units with load demand of 1263 MW and 2630 MW, respectively) to demonstrate the applicability of the proposed approach. The detailed characteristics of the units including prohibited operating zones and ramp rate limits are presented in [99] along with the convergence characteristics of the methods (FA-PSO, SOH-PSO, and PSO) tested on the systems. Test results show that FA-PSO has distinct superiority over SOH-PSO and PSO in terms of robustness, computational overhead, efficiency, and applicability to large-scale real systems.

Manteaw and Odero [100] formulated and implemented a hybridized ABC-PSO algorithm and demonstrated its successful application in the optimization of the Combined Economic and Emission Dispatch (CEED) problem. The hybrid method exploits the processing speed of PSO coupled with its convergence strength to use the results produced by ABC in yielding improved global optima.

The ABC-PSO method was tested with varying load conditions and test cases to evaluate its applicability in the CEED problem. For PSO, the maximum number of iterations and population number are considered 1000 and 15 individuals respectively, while for ABC the colony size and food number are considered 30 and 15, respectively. Though the hybrid method shows better quality solution, stable convergence characteristics and modeling flexibility with respect to other algorithms, its processing time and utility can be bettered with inclusion of mutation operators.

The hybridization of PSO with GSA reported in [103] by Dubey et al. effectively combines the exploitation ability of PSO with the exploration ability of GSA to unify their strength. The agents are initialized randomly and each agent exploring in the search space is accelerated (by means of gravity force) towards other agent having better solution (heavier mass). The agents closer to the optima proceeds slowly and assures effective exploitation. The *gbest* helps in finding the optima around a good solution. Thus the hybrid approach solved the slow speed problem of GSA algorithm on the final iterations and the problem of PSO in getting stuck at local optima.

The authors have tested the PSO-GSA hybrid algorithm in four different standard test systems, including a 6-unit system with ramp rate limits and prohibited zones, an 18-unit system with variable peak demand, a 20-unit system with transmission loss, and also a large-scale 54-unit system with valve-point loading and multiple local minima. Effect of different parameters on the performance of the algorithm was carefully studied and after considerable number of trial runs and statistical analysis the optimum parameter values selected were: n = 100, a = 10, G_0 = 1, c_1 = 2.0, c_2 = 1.5. Very elaborate comparative study is made with some of the recent reported methods with respect to (a) solution quality, (b) computational efficiency, and (c) robustness-test results show that PSO-GSA is superior in all aspects, i.e., lower average cost, less computational time, and greater consistency. Overall, the study is very convincing and performance-wise PSO-GSA can be rated high amongst the hybrid methodologies reviewed in this article.

In another study by Ashouri and Hosseini [102], hybrid PSO-GSA algorithm is successfully employed in ELD problem. Though the formulations are mostly the same as adopted by Dubey et al. [103], some improvisations are noticed in the expression of agent velocity-a new dynamic inertia weight is incorporated. With dynamic acceleration and weight coefficients, great exploration and exploitation happen in the first and final iterations of the algorithm respectively, resulting in better and faster solutions. A case study with 6-unit system considering transmission loss, prohibited zones, and ramp rate limits and also another study with 40-unit system with valve-point loading effect have been used to show the feasibility of the method. The parameter values used for the 6-unit case study were: n = 30, a = 20, G_0 = 1, c_1 = 2.5, c_2 = 0.5, and c_3 = 0.5. From comparison with the recent reported methods, it is observed that PSO-GSA approach ensures high quality and faster solution with stable convergence for ELD problem.

The results obtained by Amjadi and Sharifzadeh [104] prove that the proposed SA-CSA hybrid method is a more useful solution for the ED problem compared to other stochastic algorithms. Fast convergence and the ability of not being trapped in local optimums are undoubtedly the most important advantages of this new method. A comparison with methods reported in the literature speaks in favor of SA-CSA, though the result is not very encouraging in terms of fuel cost reduction of LD systems.

The authors believe that the CSA algorithm is flexible enough to hybridize with other stochastic search algorithms such as SA and PSO and each hybrid combination may be useful to solve ED problem.

Biswas et al. [105] have experimented hybridization involving DE in non-convex ELD problems taking into consideration transmission loss, ramp rate limits, and prohibited operating zones. The equality and inequality constraints are considered in the fitness function itself in the form of a penalty factor.

DE has outperformed powerful metaheuristic search algorithms like the GA and PSO but has certain limitations like stagnation before reaching global optima. The idea of computational chemotaxis of BFOA incorporated in DE greatly improvises the convergence characteristics of classical DE.

The proposed approach was tested with real data of 6, 13, 15, and 40 generator power systems. The results are comparable to those produced by other evolutionary algorithms. The solutions have good convergence characteristics. The authors infer that the DE-based hybrid algorithm is equally applicable to non-convex and non-smooth constrained ELD problems. However, it remains to be tested whether the method is applicable in practical large-sized problems with more realistic constraints.

Proposed hybrid approach by Malik et al. [107] combines GA with APO algorithm. The strength of GA is that it reaches the vicinity of global minima in relatively lesser time, but some of its weaknesses are: (1) solution is close to but not exactly the global minima hence not the optimal one (2) convergence speed slows down near the optimum point. Hybridization with APO helps to overcome these weaknesses. APO uses NSOA which is a classical approach for finding optimal solutions of power flow problems by minimizing the Lagrangian objective function.

The results of testing GA-APO hybrid approach on 3, 5, and 6-unit system show a significant reduction in generation cost with respect to GA. The cost reduces exponentially with increase in system size. Authors have demonstrated through simulation experiments that GA cost curve features peaks, dips, and flats in the wider band, whereas the GA-APO cost curve rise and fall in very narrow band and remains beneath the GA curve. Moreover, the solution time of the hybrid approach was found lesser than that of GA in all test cases.

In the DE-BBO hybrid method proposed by Bhattacharya and Chattopadhyay [112], the migration operator of BBO is combined with mutation, crossover, and selection operators of DE to maximize the good effect of all the operators—DE has good exploration ability in finding the region of global minima whereas BBO has good exploitation ability in global optimization problem. Together they enhance the convergence property to improve the quality of solution.

Proposed DE-BBO algorithm was tested with (i) 3-unit system (load 300 MW) with ramp rate limit and prohibited operating zone, (ii) 38-unit system with load 6000 MW, (iii) 40-unit system (load 10,500 MW) with valve-point loading, (iv) 10-unit system with load 2700 MW. The test results reveal that average costs obtained by DE-BBO for both convex and non-convex ELD problems are the least of all the reported methods. The computational time is also at par or better than the other methods. DE-BBO is also quite robust as it attains minimum cost 50 times out of 50 trials compared to 38 times in BBO. The tests point to the possibility that DE-BBO can be reliably tried to address optimization problems of complex power system in operation.

The HIGA algorithm proposed by Hosseini et al. [115] incorporates the concept of affinity factor and clonal selection of Immune System algorithm to improve the quality of solutions obtained by crossover and mutation operations of GA. The application of the hybrid approach is made in power generation system taking care of valve-point effects, prohibited operation zones, ramp rate constraints, and transmission losses. For two ELD test cases with different characteristics (studied by the authors), results yielded by HIGA method is better than that for the other methods in terms of cost and power loss. Based on the findings of the study, the authors conclude that the proposed HIGA algorithm can be effectively used to solve non-convex ELD problems in power systems.

Going beyond the single objective ELD problem, Koodalsamy and Simon [118] have attempted to solve multi-objective reliable emission and economic dispatch (REED) problem using the Fuzzified ABC or FABC algorithm. The ABC algorithm uses fuzzy membership approach to find the best compromise solution from the Pareto optimal set. The fuzzy membership of the reliability function is modeled while scheduling the optimum dispatch. The fuzzy membership function chosen for fuel cost and emission are same and it aids the ABC algorithm in maximizing the fitness function.

The FABC approach is tested on an IEEE 30-bus system and 3, 6, 10, 26 and 40-unit systems. Effect of different characteristics of the objective function and constraints are studied. To allow aberrations for the foraging behavior of bees, several test runs are carried out to set the optimal colony size and the limit value. From the results it is clear that the proposed hybrid method can yield a well distributed Pareto optimal set and is capable of finding a reasonably good compromise solution. The method is unique in the sense it can handle not only fuel cost aspect of ELD problem but at the same time emission and reliability factors which are equally important considering Kyoto Protocol 2008 and Energy Policy Act 2005. Moreover, the method is straightforward, easy to implement, and applicable for any large-scale power system.

FFA-ACO method proposed by Younes [119] is robust and can provide an optimal solution with fast computation time and a small number of iterations. In this hybrid method, the advantage that is exploited is that of using the metaheuristic methods which are very efficient and better than deterministic methods for the search of global solution for complex problems like ELD. The disadvantage of metaheuristic methods that is avoided is the relative long time of convergence owing to the high number of the agents and iterations. To further improve the efficiency of the hybrid method, FFA and ACO are used with as low as number of ants and fireflies as possible.

The author has studied two cases through simulation in MATLAB environment: Case 1 concerns the minimization of the cost function with constant losses, Case 2 concerns minimization of the cost function with variable loss. The results clearly show the effectiveness of performance of the FFA-ACO over other methods in terms of function cost value and convergence time.

The idea of a new hybrid evolutionary algorithm for solving ELD problem as proposed by the authors of this article is based on the well-known PSO and ACO algorithm. Though the authors have not applied the method in a simulated environment with real-system data, it seems to yield interesting results to be compared with those produced by other hybrid approaches. The PSO-ACO method is also expected to generate global optima in lesser time with less number of iterations. The basic idea behind the proposed hybrid algorithm is that the improvement of the *gbest* for each individual is according to the best path selection methodology of ACO. The intelligent decision-making structure of ACO algorithm is incorporated into the original PSO where the global best position is unique for every particle. PSO-ACO uses the random selection procedure of ACO algorithm to assign different global best positions to every distinct agent.

4 Conclusion

The ELD problem may be broadly classified as convex and nonconvex. In convex ELD input–output characteristics are assumed piecewise linear and monotonically increasing. The non-convex ED problem represents the complete, realistic problems having discontinuous and nonlinear characteristics owing to constraints (valve-point effect, transmission losses, ramp rate limits, and prohibited operating zones). The convex ED problem can be solved using mathematical programming-based optimization methods, but non-convex ED problem cannot be handled effectively by such classical approaches. Many heuristic search tools and soft computing approaches have been reported in the literature that addressed this problem with comparatively better result. But each approach has its inherent limitations-either they get stuck to local minima and fail to find the global minima, or converge very slowly to the solution or stagnate after certain iterations without improving solution. All these problems motivated the researchers to evolve hybrid approaches by combining a pair of compatible soft computing methods to minimize their individual weakness and in effect produce fast, accurate, and consistent solution.

Though in the literature quite a number of hybrid soft computing approaches are reported that address the issues of ED, this chapter reviews 14 selected hybrid approaches involving popular soft computing techniques. Out of these 14 approaches, 7 involve PSO technique. This indicates the modeling flexibility, consistency/reliability, and effectiveness of PSO as a hybrid component toward finding quality solution of ELD problem. GA features in three of the hybrid approaches whereas Fuzzy technique, ABC optimization, and DE each feature in two different hybrid approaches. It is difficult to adjudge the best or better approaches in solving ELD problem as each of them has been tested with varied characteristics of different power generation systems (simulated mostly in MATLAB) and have been compared with few (not all) other soft computing techniques or heuristic optimization tools or hybrid methods. There is no benchmark standard or common test data for comparing the simulation results obtained using different hybrid methods. Still PSO-GA hybrid combination proposed by Younes and Benhamida [96] and PSO-GSA approach by Dubey et al. and also by Ashouri and Hosseini appears superior over many other hybrid approaches in terms of lower average cost, sure and fast convergence, greater consistency, and less computational time. The PSO-ACO method proposed by the present authors is expected to overcome common limitations of many hybrid approaches involving PSO but it is yet to be tested with real data. Among methods not featuring PSO, DE-BBO method proposed by Bhattacharya and Chattopadhyay [112] and FABC algorithm proposed by Koodalsamy and Simon [118] are very promising. All the other hybrid methods discussed in this chapter are, however, unique in their approaches and indeed have some advantages over the rest.

The ELD problem for small-scale to large-scale systems has been greatly optimized by virtue of competing research in the field, evolving new optimization methods-particularly, the latest hybrid soft computing approaches. But after going through the recent and past research endeavors, the authors strongly feel that there is enough scope for research to address the challenges of future related to power system and allied aspects. 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).

References

1. Grigsby LL (2009) Power System Stability and Control. CRC Press, New York
2. Wood AJ, Woollenberg BF, Sheble GB (1984) Power generation operation and control. Wiley Publishers, New York
3. Yare Y, Venayagamoorthy GK, Saber AY (2009) Conference: economic dispatch of a differential evolution based generator maintenance scheduling of a power system. In: Power & Energy Society General Meeting, 2009 (PES '09), IEEE
4. Chowdhury BH, Rahman S (1990) A review of recent advances in economic dispatch. IEEE Trans Power Syst 5(4):1248–1259
5. Garg M, Kumar S (2012) Int J Electron Commun Technol IJECT 3(1)
6. Lee KY et al (1984) Fuel cost minimize at ion for both real-and reactive power dispatches. Proc Inst Elect Eng Gen Trans Distrib 131(3):85–93
7. Sailaja Kumari M, Sydulu M (2009) A fast computational genetic algorithm for economic load dispatch. Int J Recent Trends Eng 1(1)
8. Naveen Kumar KP, Parmar S, Dahiya S (2012) Optimal solution of combined economic emission load dispatch using genetic algorithm. Int J Comput Appl (0975–8887) 48(15)
9. Chopra L, Kaur R (2012) Economic load dispatch using simple and refined genetic algorithm. Int J Adv Eng Technol 5(1):584–590
10. Biswas SD, Debbarma A (2012) Optimal operation of large power system by GA method. J Emerg Trends Eng Appl Sci (JETEAS) 3(1):1–7
11. Anuj Gargeya1 M, Pabba SP (2013) Economic load dispatch using genetic algorithm and pattern search methods. Int J Adv Res Electr Electron Instrum Eng 2(4) 2013
12. Arora D, Sehgal S, Kumar A, Soni A (2013) Economic load dispatch using genetic algorithm. Int J Techn Res (IJTR), 2(2)
13. Kapadia RK, Patel NK (2013) J Inform Knowl Res Electr Eng 2:219–223
14. Mansour WM, Salama MM, Abdelmaksoud SM, Henry HA (2013) Dynamic economic load dispatch of thermal power system using genetic algorithm. IRACST—Eng Sci Technol: An Int J (ESTIJ) 3(2). ISSN:2250–3498
15. Jain AK, Mandloi T Comparison of classical method and soft computing optimization algorithm applied to economic load dispatch problem. Int J Latest Trends Eng Technol (IJLTET) 3(4)
16. Aliyari H, Effatnejad R, Areyaei A (2014) Economic load dispatch with the proposed GA algorithm for large scale system. J Energy Natural Resour 3(1):1–5
17. Park J-B, Lee K-S, Shin J-R, Lee K-Y (2005) A particle swarm optimization for economic dispatch with nonsmooth cost functions. IEEE Trans Power Syst 20(1)
18. Mahadevan K, Kannan PS, Kannan S (2005) Particle swarm optimization for economic dispatch of generating units with valve-point loading. J Energy Environ 4:49–61

19. Sudhakaran M, Ajay P, Vimal Raj D, Palanivelu TG (2007) Application of particle swarm optimization for economic load dispatch problems. In: The 14th international conference on intelligent system applications to power systems, ISAP 2007, Kaohsiung, Taiwan
20. dos Santos Coelho L, Lee C-S (2008) Solving economic load dispatch problems in power systems using chaotic and Gaussian particle swarm optimization approaches. Electrical Power Energy Syst. 30:297–307
21. Baskar G, Mohan MR (2008) Security constrained economic load dispatch using improved particle swarm optimization suitable for utility system. Electric Power Energy Syst 30:609–613
22. Mahor A, Prasad V, Rangnekar S (2009) Economic dispatch using particle swarm optimization: a review. Renew Sustain Energy Rev 13:2134–2141
23. Vlachogiannis JG, Lee KW (2009) Economic load dispatch-a comparative study on heuristic optimization techniques with an improved coordinated aggregation-based PSO. IEEE Trans Power Syst 24(2)
24. Saber AY, Chakraborty S, Abdur Razzak SM, Senjyu T (2009) Optimization of economic load dispatch of higher order general cost polynomials and its sensitivity using modified particle swarm optimization. Electric Power Syst Res 79:98–106
25. Muthu Vijaya Pandian S, Thanushkodi K (2010) Solving economic load dispatch problem considering transmission losses by a Hybrid EP-EPSO algorithm for solving both smooth and non-smooth cost function. Int J Comput Electr Eng 2(3):1793–8163
26. Muthu S, Pandian V, Thanushkodi K (2011) An efficient particle swarm optimization technique to solve combined economic emission dispatch problem. Eur J Sci Res 54(2):187–192
27. Batham R, Jain K, Pandit M (2011) Improved particle swarm optimization approach for nonconvex static and dynamic economic power dispatch. Int J Eng Sci Technol 3(4):130–146
28. Sreenivasan G, Dr Saibabu CH, Dr Sivanagaraju S (2011) Solution of dynamic economic load dispatch (DELD) problem with valve point loading effects and ramp rate limits using PSO. Int J Electr Comput Eng 1(1):59–70
29. Khokhar B, Singh Parmar KP (2012) A novel weight-improved particle swarm optimization for combined economic and emission dispatch problems. Int J Eng Sci Technol (IJEST) 4 (05) 2012
30. Anurag Gupta KK, Wadhwani SK (2012) Combined economic emission dispatch problem using particle swarm optimization. Int J Comput Appl 49(6):0975–8887
31. Hardiansyah J, Yohannes MS (2012) Application of soft computing methods for economic load dispatch problems. Int J Comput Appl 58(13):0975–8887
32. Chakrabarti R, Chattopadhyay PK, Basu M, Panigrahi CK (2006) Particle swarm optimization technique for dynamic economic dispatch. IE(I) J-EL 87:48–54
33. Agrawal S, Bakshi T, Majumdar D (2012) Economic load dispatch of generating units with multiple fuel options using PSO. Int J Control Autom 5(4)
34. Linga Murthy KS, Subramanyam GVS, SriChandan K (2012) Combined economic and emission dispatch for a wind integrated system using particle swarm optimization. Int Electr Eng J (IEEJ) 3(2):769–775
35. Junaidi H, Yohannes MS (2012) Intell Syst Appl 12:12–18
36. Sharma J, Mahor A (2013) Particle swarm optimization approach for economic load dispatch: a review. Int J Eng Res Appl (IJERA) 3(1):013–022
37. Niknam T (2006) An approach based on particle swarm optimization for optimal operation of distribution network considering distributed generators. In: Proceedings of the 32nd annual conference on IEEE industrial electronics, IECON 2006, pp 633–637 1942–1948
38. Soubache ID, Ajay-D-Vimal Raj P (2013) Unified particle swarm optimization to solving economic dispatch. Int J Innov Technol Explor Eng (IJITEE) 2(4)
39. Tiwari S, Kumar A, Chaurasia GS, Sirohi GS (2013) Economic load dispatch using particle swarm optimization. Int J Appl Innov Eng Manag 2(4)

40. Singh N, Kumar Y (2013) Economic load dispatch with valve point loading effect and generator ramp rate limits constraint using MRPSO. Int J Adv Res Comput Eng Technol (IJARCET) 2(4)
41. Venkatesh B, Subbu Chithira Kala V (2013) A particle swarm optimization for multiobjective combined heat and power economic dispatch problem considering the cost, emission and losses. Int J Scient Eng Res 4(6) 2013
42. Md. Khan J, Mahala H (2013) Applications of particle swarm optimization in economic load dispatch. In: Proceedings of national conference on recent advancements in futuristic technologies (NCRAFT 13), vol 1, Issue 1, PAPER ID 0072, Oct-2013
43. Singh Maan R, Mahela OP, Gupta M (2013) Solution of economic load dispatch problems with improved computational performance using particle swarm optimization. Int J Eng Sci Invent 2(6) 01–06
44. Singh N, Kumar Y (2013) Constrained economic load dispatch using evolutionary technique. Asian J Technol Manage Res 03(02)
45. Sinha P (2013) Particle swarm optimization for solving economic load dispatch problem. Int J Commun Comput Technol 01(63)
46. Singh M, Thareja D (2013) A new approach to solve economic load dispatch using particle swarm optimization. Int J Appl Innov Eng Manage (IJAIEM) 2(11)
47. Niknam T, Amiri B, Olamaie J, Arefi A (2008) An efficient hybrid evolutionary optimization algorithm based on PSO and SA for clustering. J Zhejiang University Sci A. doi:10.1631/jzus.A0820196
48. Tikalkar A, Khare M (2014) Economic load dispatch using linearly decreasing inertia weight particle swarm optimization Int J Emerg Technol Adv Eng 4(1)
49. Abdullah MN, Bakar AHA, Rahim NA, Mokhlis H, Illias HA, Jamian JJ (2014) Modified particle swarm optimization with time varying acceleration coefficients for economic load dispatch with generator constraints. J. Electr Eng Technol 9(1):15–26
50. Sarath Babu G, Anupama S, Suresh Babu P (2014) Int J Eng Res Develop 9(11):15–23
51. Chaturvedi N et al (2014) A novel approach for economic load dispatch problem based on GA and PSO. Int J Eng Res Appl 4(3):24–31
52. Sivaraman P, Manimaran S, Parthiban K, Gunapriya D (2014) PSO approach for dynamic economic load dispatch problem. Int J Innov Res Sci Eng Technol 3(4)
53. Mistry P, Vyas S (2014) A study on: optimisation of economic load dispatch problem by PSO. Indian J Appl Res 4(6)
54. Khan S, Gupta C (2014) An optimization techniques used for economic load dispatch. Int J Adv Technol Eng Res (IJATER) 4(4)
55. Sinha N, Chakrabarti R, Chattopadhyay PK (2003) Evolutionary programming techniques for economic load dispatch. IEEE Trans Evol Comput 7(1)
56. Nomana N, Iba H (2008) Differential evolution for economic load dispatch problems. Electr Power Syst Res 78:1322–1331
57. Surekha P, Sumathi S (2012) Solving economic load dispatch problems using differential evolution with opposition based learning. WSEAS Trans Inf Sci Appl 9(1)
58. Soni SK, Bhuria V (2012) Multi-objective emission constrained economic power dispatch using differential evolution algorithm. Int J Eng Innov Technol (IJEIT) 2(1)
59. Kumar C, Alwarsamy T Solution of economic dispatch problem using differential evolution algorithm. Int J Soft Comput Eng (IJSCE) 1(6)
60. Balamurugan K, Krishnan SR (2013) Differential evolution based economic load dispatch problem. In: Proceedings of 1st national conference on advances in electrical energy applications, 3–4 Jan 2013
61. Pramod Kumar Gouda, PK, Raguraman H (2013) Economic load dispatch optimization in power system with renewable energy using differential evolution algorithm. In: Proceedings of national conference on advances in electrical energy applications, Jan 3–4 2013
62. Baijal A, Chauhan VS, Jayabarathi T (2011) IJCSI Int J Comput Sci 8(4):1
63. Tankasala GR Artificial bee colony optimisation for economic load dispatch of a modern power system. Int J Sci Eng Res 3(1)

64. Bommirani B, Thenmalar K (2013) Optimization technique for the economic dispatch in power system operation. Proceedings of national conference on advances in electrical energy applications, Jan 3–4 2013
65. Musirin I et al (2008) Ant colony optimization (ACO) technique in economic power dispatch problems. In: Proceedings of the international multi-conference of engineers and computer scientists (IMECS), vol 2I, Hong Kong 19–21 March 2008
66. Rahmat NA, Musirin I, Abidin AF (2013) Differential evolution immunized ant colony optimization (DEIANT) technique in solving weighted economic load dispatch problem. Asian Bull Eng Sci Technol (ABEST) 1(1):17–26
67. Effatnejad R, Aliyari H, Tadayyoni, Abdollahshirazi A (2013) Int J Techn Phys Probl Eng (IJTPE) 5(15):2
68. Rahmat NA, Musirin I (2013) Differential evolution immunized ant colony optimization technique in solving economic load dispatch problem. Sci Res 5(1B)
69. Vasovala PJ, Jani CY, Ghanchi VH, Bhavsar PHK (2014) Application of ant colony optimization technique in economic load dispatch problem for IEEE-14 Bus System. IJSRD —Int J Sci Res Dev 2(2)
70. Mishra NK et al (2011) Economic dispatch of electric power using clone optimization technique. Elixir Electr Eng 40:5155–5158
71. Padmini S, Sekhar Dash S, Vijayalakshmi, Chandrasekar S (2013) Comparison of simulated annealing over differential evolutionary technique for 38 unit generator for economic load dispatch problem. In: Proceedings of national conference on advances in electrical energy applications, 3–4 Jan 2013
72. Swain RK, Sahu NC, Hota PK (2012) Gravitational search algorithm for optimal economic dispatch. In: 2nd international conference on communication, computing and amp; security, vol 6, pp 411–419
73. Serapião ABS (2013) Cuckoo search for solving economic dispatch load problem. Intell Control Autom 4(4):385–390
74. Tomassini M (1999) Parallel and distributed evolutionary algorithms: a review. In: Miettinen K, M¨akel¨a M, Neittaanm¨aki P, Periaux J (eds) Evolutionary algorithms in engineering and computer science, pp 113–133. Wiley, Chichester
75. Nada MA, AL-Salami N (2009) System evolving using ant colony optimization algorithm. J Comput Sci 5(5):380–387
76. Dorigo M, Ganbardella L (1997) Ant colony system: a cooperative learning approach to the traveling salesman problem. IEEE Trans Evol Comput 1(1):53–66
77. Younes M, Hadjeri S, Zidi S, Laarioua S (2009) Economic power dispatch using an ant colony optimization method. In: The 10th international conference on sciences and techniques of automatic control & computer engineering ~ STA, Hammamet, Tunisia, pp 20–22, Dec 2009
78. Dorigo M (1992) Optimization, learning and natural algorithms. PhD Thesis, Dipartimento di Elettronica, Politecnico di Milano, Italy
79. Sonmez Y (2011) Multi-objective environmental/ economic dispatch solution with penalty factor using Artificial Bee Colony algorithm. Sci Res Essays 6(13):2824–2831
80. Sudhakara Reddy K, Damodar Reddy M (2012) Economic load dispatch using firefly algorithm. Int J Eng Res Appl (IJERA) 2:2325–2330
81. Apostolopoulos T, Vlachos A (2011) Application of the firefly algorithm for solving the economic emissions load dispatch problem. Int J Comb 1(3):1–23
82. Wood, AJ, Wollenberg BF (1984) Example problem 4e. Power Generation, Operation and Control, pp 85–88. Wiley
83. Bhattacharya A, Chattopadhyay PK (2010) Biogeography-based optimization for different economic load dispatch problems. IEEE Trans Power Syst 25:1064–1073. http://ieeexplore.ieee.org/xpl/tocpreprint.jsp
84. Rashedi E, Saryazdi S (2009) GSA: a gravitational search algorithm. Inf Sci 179:2232–2248

85. Farhat IA, Hawary E (2012) Multi-objective economic-emission optimal load dispatch using bacterial foraging algorithm. In: 25th IEEE Canadian conference on electrical and computer engineering (CCECE)
86. Passino KM (2002) Biomimicry of bacterial foraging for distributed optimization and control. IEEE Control Syst Magaz 22(3):52–67
87. Aruldoss Albert Victoire T, Ebenezer Jeyakumar A (2003) Hybrid PSO-DS for non-convex economic dispatch problems. In: Digest of the proceedings of the WSEAS conferences, Nov 2003
88. Lee SC, Kim YH (2002) An enhanced Lagrangian neural network for the ELD problems with piecewise quadratic cost functions and nonlinear constraints. Electr Power Syst Res 60:167–177
89. Won J-R, Park Y-M (2012) Economic dispatch solutions with piece-wise quadratic cost functions using improve genetic algorithm. Electr Power Energy Syst 25:355–361
90. Park JH, Yang SO, Lee HS, Park M (1996) Economic load dispatch using evolutionary algorithms. IEEE Proc 441–445
91. dos Santos Coelho L, Mariani VC (2007) Economic dispatch optimization using hybrid chaotic particle swarm optimizer. In: IEEE international conference systems, man and Cybernetics, ISIC 2007
92. Bertsekas DB (1976) On the Goldstein-Levitin-Polyak gradient projection method. IEEE Trans Autom Control 21(2):74–184
93. Hénon MA (1976) A two-dimensional mapping with a strange attractor. Commun Math Phys 50:69–77
94. Reynolds RG (1994) An introduction to cultural algorithms. In: Proceedings of the third annual conference on evolutionary programming, SanDiego, CA, USA, pp 131–139
95. Muthu Vijaya Pandian S, Thanushkodi K (2010) Int J Comput Electr Eng 2(3):1793–8163
96. Younes M, Benhamida F (2011) PRZEGLĄD ELEKTROTECHNICZNY (Electrical Review), ISSN:0033-2097, R. 87 NR 10/2011
97. Younes M, Hadjeri S, Zidi S, Houari S, Laarioua M (2009) Economic power dispatch using an ant colony optimization method. In: 10th International conference on sciences and techniques of automatic control & computer engineering, Hammamet, Tunisia, pp 785–794 Dec 20–22
98. Bouzeboudja H, Chaker A, Allali A, Naama B (2005) Economic dispatch solution using a real-coded genetic algorithm. Acta Electrotechnica et Informatica 5(4)
99. Soni N, Dr Pandit M (2012) A fuzzy adaptive hybrid particle swarm optimization algorithmt to solve non-convex economic dispatch problem. Int J Engineering Innov Technol (IJEIT) 1 (4)
100. Manteaw ED, Abungu Odero N (2012) Multi-objective environmental/economic dispatch solution using ABC_PSO hybrid algorithm. Int J Sci Res Publ 2(12)
101. Bharathkumar S, Arul Vineeth AD, Ashokkumar K, Vijay Anand K (2013) Multi objective economic load dispatch using hybrid fuzzy, bacterial Foraging-Nelder–Mead algorithm. Int J Electr EngTechnol 4(3):43–52
102. Ashouri M, Hosseini SM (2013) Application of new hybrid particle swarm optimization and gravitational search algorithm for non convex economic load dispatch problem. J Adv Comput Res Quart 4(2):41–51
103. Dubey HM, Pandit M, Panigrahi BK, Udgir M (2013) Economic load dispatch by hybrid swarm intelligence based gravitational search algorithm. Int J Intell Syst Appl 5(08):21–32
104. Amjadi N, Sharifzadeh H (2010) Solution of nonconvex economic dispatch problem considering valve loading effect by a new modified differential evolution algorithm. Electr Power Energy Syst
105. Biswas A (2009) Hybrid artificial intelligence systems lecture notes in computer science 5572:252–260
106. Lampinen J, Zelinka I (2000) On stagnation of the differential evolution algorithm. In: Proceedings of MENDEL, 6th International Mendel Conference on Soft Computing, Brno, Czech Republic

107. Nadeem Malik T, ul Asar A, Wyne MF, Akhtar S (2010) A new hybrid approach for the solution of nonconvex economic dispatch problem with valve-point effects. Electr Power Syst Res 80(9):1128–1136
108. Malik TN, Abbasi AQ, Ahmad A (2006) Computational framework for power economic dispatch using genetic algorithm. In: Proceeding of the third international conference on informatics in control, automation and robotics (ICINCO), pp 191–194. Stubal, Portugal, Aug 1–5
109. Wood AJ, Wollenberg BF (1996) Power Generation Operation and Control. John Wiley, New York
110. Pai MA (2006) Computer techniques in power system analysis. Tata McGraw-Hill, New Delhi
111. Narayana PP, Latha K (2004) Evolutionary programming based economic power dispatch solutions with independent power producers. In: IEEE international conference on electric utility deregulation, restructuring and power technologies (DRPT), pp 172–177
112. Bhattacharya A, Chattopadhyay PK (2010) Hybrid differential evolution with biogeography based optimization for solution of economic load dispatch. IEEE Trans Power Syst 25(4)
113. Selvakumar I, Thanushkodi K (2007) A new particle swarm optimization solution to nonconvex economic dispatch problems. IEEE Trans Power Syst 22(1):42–51
114. Chiang CL (2005) Improved genetic algorithm for power economic dispatch of units with valve-point effects and multiple fuels. IEEE Trans Power Syst 20(4):1690–1699
115. Hosseini MM, Ghorbani H, Rabii A, Anvari Sh (2012) A novel heuristic algorithm for solving non-convex economic load dispatch problem with non-smooth cost function. J Basic Appl Sci Res 2(2):1130–1135
116. Soroudi A, Ehsan M, Zareipour H (2011) A practical eco-environmental distribution network planning model including fuel cells and non-renewable distributed energy resources. Renew Energy 36:179–188
117. Jain LC, Palade V, Srinivasan D (2007) Advances in evolutionary computing for system design. In: Studies in computational intelligence, vol 66. Springer
118. Koodalsamy C, Simon SP (2013) Fuzzied artificial bee colony algorithm for nonsmooth and nonconvex multiobjective economic dispatch problem. Turkish J Electr Eng Comput Sci 21:1995–2014
119. Younes M (2013) A novel hybrid FFA-ACO algorithm for economic power dispatch. Control Eng Appl Inf 15(2):67–77
120. Sayah S, Zehar K (2008) Modified differential evolution algorithm for optimal power flow with non-smooth cost functions. Energy Convers Manag 49:3036–3042

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Hybrid Soft Computing Approaches
Research and Applications
Bhattacharyya, S.; Dutta, P.; Chakraborty, S. (Eds.)
2016, XIV, 457 p. 154 illus., Hardcover
ISBN: 978-81-322-2543-0