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Combined emission economic load dispatch problem using hybrid combination of flower pollination algorithm and moderate random search particle swarm optimization

Jaspreet Singh
dandiwal0786@gmail.com
Adesh Institute of Engineering and Technology, Faridkot, Punjab

Puneet Jain
puneetjain988@gmail.com
Adesh Institute of Engineering and Technology, Faridkot, Punjab

Jaspreet Singh
dandiwal0786@gmail.com
Adesh Institute of Engineering and Technology, Faridkot, Punjab

ABSTRACT

The total cost of electricity generation is minimized while fulfilling the total load demand and considering all constraints in the Combined Economic Emission Dispatch (CEELD) problem. Electricity generation from fossil fuel negatively impacts the environment. Therefore, various optimization techniques have been deployed for the CEELD problem. In the literature, the Modified Random Search Particle Swarm Optimization (MRSPSO) and Flower pollination algorithm (FPA) are used as a solution for CEELD known as Combined Economic Emission Load dispatch problem. However, MRSPSO is easy to settle into local optima in high-dimensional space and delivers a low convergence rate in the iterative process, whereas in the FPA, the diverse population makes it prone to being limited to the local optima. Thus, in order to overcome these limitations, in this paper, we have hybrid the FPA and MRSPSO algorithm that improves the convergence rate to meet the optimal solution. Initially, we have implemented MRSPSO and FPA algorithm; after that, combined it for CEELD. The experimental results were performed in MATLAB. The experimental results show that the hybrid approach gives better results as compared to the MRSPSO and FPA. Thus, the proposed technique is efficient and can be deployed for real-time CEELD problem.

Keywords: *Particle Swarm Optimization, Flower Pollination Algorithm, Combined Economic Emission Load Dispatch, Modified Random Search Particle Swarm Optimization, MRSPSO, FPA, Economic Load Dispatch*

1. INTRODUCTION

The interconnected Electric utility system is required to achieve load demand, better working conditions to satisfy operational constraints, high reliability, and low production cost. The main requirement of the low cost operating fuel for the unit is attained by estimating electrical loads in means of KVA, KW, and KVAR and by scheduling economic distribution between various parallel co-generating units. The total spontaneous losses and corresponding total generation demand are calculated by this inequality and equality limitations. The scheduling of load allows reactive and real power generators to meet them is important for the demand of low cost within specific limits to provide introductory facts about voltage level in the organization and moreover, shows a significant part in studying power system and design equipment activities. The generator's cost functions using quadratic functions are approximated with rising curves cost for direct functions, different elements contributing in load resource of optimal generation and energy management in real-time towards power system control are required for ELD problem optimization. Higher-order discontinuities and nonlinearities are showed by valve point stacking genuine information yield associated. Lambda iteration method, dynamic and quadratic programming [3-5], gradient-based method [1, 2], unit commitment or even Newtonian methods [6-8], integer, nonlinear, linear are methods required to trade-in complex algorithms as linear programming techniques do not only have some constraints with non-negative elements but also are hard and consistent. Quadratic programming associated with piecewise quadratic cost approximation is the demerits that are noticed. Also, it is noticed that the Newton-based strategy has drawback of convergence characteristics but its initial eradication and optimal criteria suffer a poor extent. Different day to day methods such as optimal power flow (OPF), simulated annealing (SA), pattern search (PS), evolutionary programming (EP), genetic algorithm (GA), tabu search (TS), particle swarm optimization (PSO), neural work and differential evolution (DE) are implemented and developed by various researchers [9-20] in order to overcome the difficulties that are faced by various conventional methods. Genetic algorithms, simulation annealing are time-consuming evolutionary programs and modern techniques that are studied. Therefore methods like DE, TS traps the computing process at relative optima and are also tough in defining memory associated when used.

PSO is influenced by the collective behavior of social animals or the collective actions of bird flocking that is included in optimization methods. Therefore characterizing ways lead by the neighbor's and their own specific manifestations. ELD and CEED issues in power plants are solved by using a valve-point loading effect by executing MRSPSO and FPA with ramp rate limit restraint in this research. Different power demands to have a low cost of generation units are compared as a result of the various unit test systems to satisfy the high and low limits of a generator for power need.

2. PROBLEM FORMULATION

2.1 Economic Dispatch Basics

To meet the load demand not only low-cost power generation is considered also low-cost fuel with respect to restraints is considered.

2.2 Objective Function

$$F_t = \left(\sum_{i=1}^{n} F_i P_i\right) = \left(\sum_{i=1}^{n} a_i P_i^2 + b_i P_i + c_i\right) \quad (1)$$

Discontinuity and nonlinearity of Economic load dispatch increase owing to the existence of valve point loading outcome, thus unbiased task can be written as:

$$F_t = \sum_{i=1}^{n} a_i P_i^2 + b_i P_i + c_i + |\, e_i * \sin f_i * (P_i^{min} - P_i) \quad (2)$$

Where

F_t - The function,

a_i, b_i, c_i - The cost coefficients

e_i, f_i - The valve point loading effect coefficient of the ith generator.

2.3 Constraints

Model with constraints in subjects are considered as mentioned below.

2.3.1 Real Power Balance

Total power generated = (load Demand) + (Losses)

$$\sum_{i=1}^{n} P_i - P_D - P_L = 0 \quad (3)$$

$$P_L = \sum_{i=1}^{n} \sum_{j=1}^{n} P_i B_{ij} P_j + \sum_{i=1}^{n} B_{0i} P_i + B_{00} \quad (4)$$

Where,

P_D - The total system demand

P_L - The total line loss

B_{ij} - The symmetric matrix (B), containing loss coefficient

B_{i0} - The loss coefficient of the ith element

B_{00} - The loss coefficient constant

2.3.2 Operating Limits: The power should not be below the required stable working limit when delivered by the unit and it should between higher and lower limits that is

$$P_{imin} \leq P_i \leq P_{imax} \quad (5)$$

Where,

P_i - ith generator's power output

P_{imin} - ith generator's minimum power output

P_{imax} - ith generator's maximum power outputs

2.3.3 Ramp Rate Limits: The rise and fall in operating condition is considered as ramp rate limit constraints as follow:

$$(t)+(t-1) \leq UR_i \quad (6)$$

$$(t-1) - (t) \geq DR_i \quad (7)$$

The output and functioning boundary finish of every division is dependent on high/low rate of time per hour. Therefore,

$$(t) = \max\,(P_{imin}, P_i(t-1) - DR_i) \quad (8)$$

$$(t) = \min\,(P_{imax}, P_i(t-1) - UR_i) \quad (9)$$

$$(t) \leq (t) \leq P_{imax}(t) \quad (10)$$

Where,

P_{it} - Output power current of the ith unit

$P_i\,(t-1)$ as ith generator operating point in previous.

UR_i as up ramp and DR_i as down ramp of ith generator in MW per time-period for the rate limit.

3. OVERVIEW OF PSO AND FPA STRATEGIES

In this section, PSO policies to resolve issues related to the power structure and economic load dispatch are reviewed that are implemented by various researchers. The performance measures of the MRSPSO method are compared here with our research to earlier researchers.

3.1 Standard Particle Swarm Optimization

The optimization technique avoiding direct recombination of the genetic matter is based on population and self-adaptive PSO. In exploration space, the search is loaded by a inhabitants of casual results and there are no development workers as transmutation limit in Evolutionary Computation methods whereas the common conduct of a particle in the swarm is considered in the PSO algorithm. At each time of generation, the best global solution is to find an adjustment in the trajectory of each distinct towards its best particle of the swarm and its own location. To find a logical and quick solution, bird flocking 2D space simulation PSO technique is developed. Sx and Sy, Vx, and Vy in the X-Y plane is used to represent the position and velocity of each particle. The best value calculated from this information in the group and describes the performance of other neighboring particles where Gbest and Pbest describe the personal experience and similarity knowledge of each particle. The position can be modified by seeing present locations (Sx, Sy) and (Vx, Vy) velocity between Pbest-individual intelligence and Gbest-group intelligence of each particle. Position and velocities computed in X-Y plane are computed using following equations:

$$V_i^{k+1} = W \times V_i^k + C_1 \times rand_1 \times (P_{besti} - S_i^k) + C_2 \times rand_2 \times (G_{best} - S_i^k) \quad (11)$$

$$S_i^{k+1} = S^{\,k} + V^{k+1} \quad (12)$$

Where

V_i^{k+1} - velocity of ith individual at (k + 1)th iteration

V_i^k - velocity of ith individual at kth iteration

W - Inertia weight

C_1, C_2 - acceleration coefficients

$rand_1$, $rand_2$ - random numbers selected between 0 and1.

P_{besti} - Finest position of the ith individual

G_{best} - best position among the individuals (group best)

S_i^{k+1} - position of ith individual at (k + 1) th iteration

S_i^k - position of ith individual at kth iteration.

Velocity of each particle is modified according to equation (3.15), within high and low velocity limits V_{min} and V_{max} respectively. To enable quick convergence equation 3.16 is used to modify inertia weight 'W'.

$$W = W_{max} - \frac{(W_{max}-W_{min})}{iter} * iter \quad (13)$$

Where
W_{max} - Initial value of inertia weight
W_{min} - Final value of inertia weight
Iter - Current iteration number
$iter_{max}$ - Maximum iteration number
C_1 and C_2 - acceleration coefficients

The required momentum for particles to move across space is provided by the previous velocity that is the first part of the equation (1.1). The movement towards their best position is encouraged by the cognitive element of the second part that signifies the previous individual intellectual of all particles. The collaborative effect of particle that pulls it towards the best global particle in the third part called a social element and also the global optimal solution is found with its help. High diversity is considered during the early part of the search during the optimization process where the local and global search is balanced by inertia weight W. Thus by varying inertia weight linearly over generations, convergence can be significantly improved by using the PSO method.

3.2 Moderate Random Search Particle Swarm Optimization

MRSPSO method that is modified particle swarm optimizer is presented that progresses the ability of swarms by raising the rate of making and merging solution space effectively. The algorithm performance that enhance by position updating and no velocity updating is needed is proposed in MRSPSO strategy.

$$S_i(k+1) = P_d + \alpha.\lambda\,(m_{besti} - S_{IK}) \qquad (14)$$

$$m_{besti} = \sum_{i=1}^{n} \frac{P_{best}}{S} \qquad (15)$$

Where
S = MRPSO's population size
α = the parameters attained by varying α from 0.45 to 0.35 with linearly-decreasing procedure through amidst rotations
$S_i(k+1)$ = position of ith particle at (k+1)th iteration
P_d = the attractor moving direction of a particle
P_d = rand*P_{best} + (1-rand)*g_{best}

3.3 Flower Pollination Algorithm

In 2012, FPA was urbanized by Xin-She Yang as being influenced by nature pollination and flowering plants. Many biological systems developed with appealing and amazing efficiency to attain their reproduction objectives from billions of years as nature has solved demanding difficulties. Over the previous few spans, many nature-inspired algorithms and biological rules are characterized by researchers [8]. For instance, the firefly algorithm created on blinking well-lit designs of tropic fireflies whereas GA created on the Darwinian evolution of organic classifications and PSO based on swarm behavior of birds and fish. The infield of engineering and industry these algorithms have a wider area of applications in multi-target Real-world pattern issues and their multi targets generally conflict with each other and have dimensionality, homogeneity, and time complexity as added challenges that are frequently more time-consuming.

3.4 Formulation using FPA

Three rules that are important for the formulation of FPA are as follow:

- Global pollination represents pollen carried by pollinators in cross-pollination and biotic pollination following levy flight with their flights.
- Local pollination does not need any pollinators to represent abiotic and self- pollination.
- Controlling factor p $\in [0, 1]$ is an important factor to control all pollination interactions.

The above steps are used to generate efficiently updated equations in order to receive updated formulas. Bees are required as pollinators to carry pollen from flowers and deliver to long distances in huge range as in universal pollination phase. Thus local pollination and universal pollination steps are represented as:

Global Pollination:

X_i^(t+1)= X_i^t+ γ.L.λ.(g^*- X_i^t) (16)

Where

X_i^(t+1) = Next Position
X_i^t = Current Position
L = Levy Distribution
g^* = Best Position
γ = scaling factor controlling the step size

L is the levy flight step size that represents pollination strength. To imitate the way insects behave while traveling over a great space levy journey can be represented as:

Beta = 3/2 (17)

Temp div = gamma ((1=beta/2)*beta*2^((beta-1)/2))^(1+beta)) (18)

Sigma = gamma (1+beta)*sin (pi*beta/2)/temp div) (19)

u = randn (1, d)*sigma (20)

v = u./abs(v).^(1/beta) (21)

L = 0.01*step (22)

3.5 Hybrid Approach FPA and MRPSO

The FPA algorithm offers numerous advantages over existing optimization algorithms, such as only one control parameter and offers a balanced intensification and diversification of solutions through the adoption of levy flight. Besides that, the diverse population negatively impacts the local optima. Therefore, in this paper, we have hybrid the FPA algorithm with MRPSO in order to improve it. The flowchart of the hybrid approach is shown in Figure 1. Initially, various parameters defined, such as power plant limits, fuel coefficient, and loss coefficient. Next, Initialize the population and fitness function. After that, calculate the fitness function of the initial population. Then, update the population with FPA based on fitness function and the best value stored. On the updated population, the MRPSO algorithm applied, and the best solution determined in the output. The whole process is iterated for a fixed number of iterations.

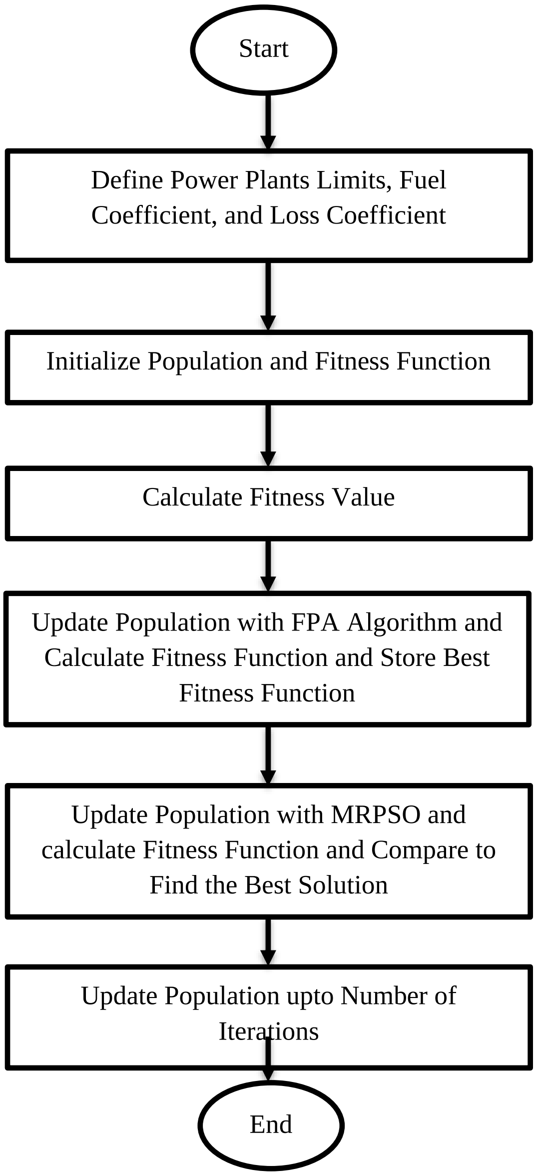


Fig. 1: Flowchart of the Hybrid Approach of FPA and MRPDO

4. EXPERIMENTAL RESULTS AND DISCUSSION

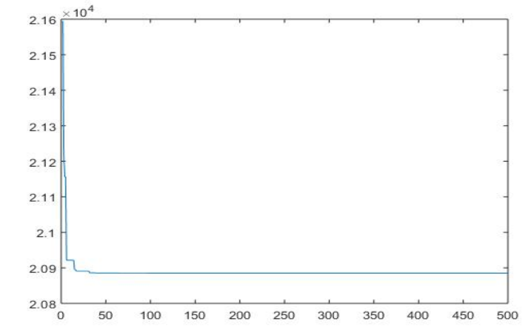
In this section, in order to validate the proposed technique, the experimental results were performed while considering different cases. The algorithm is written and simulated in MATLAB. Next, we have explained the different case studies for MRPSO, FPA, and its hybrid approach.

Case 1: In the case of 400 MW, a three-unit system without emission of power demand is considered. In Table 1, we have shown the power output parameters for MRPSO, FPA, and its hybrid approach.

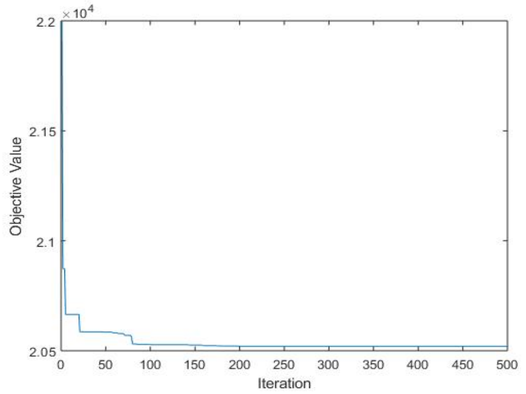
Table 1: Objective Function Vs. Number of Iterations Graph for MRPSO, FPA, and Hybrid FPA-MRPSO Algorithm

Power Output (MW)	MRPSO	FPA	Hybrid FPA and MRPSO
P1	90.7936	113.1384	107.9031
P2	191.7296	160.4264	164.4466
P3	125.0000	133.7787	134.7763
PLOSS(MW)	7.5233	7.3434	7.1259
Total Cost ($)	20834.9954	20520.0362	20510.78

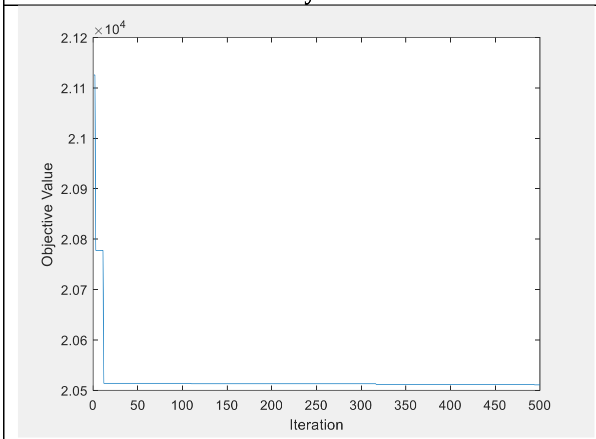
The results show that the total cost for electricity generation is less for the hybrid approach as compared to MRPSO and FPA with fewer power losses (PLOSS). Further, we have drawn the objective function vs. the number of iterations graph for the MRPSO, FPA, and hybrid FPA and MRPSO approaches in Table 2. The results show that the hybrid approach meets the objective function in a lesser iteration as compared to the other.



(a) Using MRPSO for the three-unit system for generation cost



(b) Using FPA for the generation cost of the three-unit system



(c) Hybrid method MRPSO and FPA a three-unit system for generation cost

5. CONCLUSION

In this paper, we have hybrid the two-optimization algorithms, FPA and MRPSO, in order to reduce the power losses, cost factor and improves the convergence rate to meet the objective function. Initially, we have implemented the FPA and MRPSO algorithm. After that, hybrid it. The experimental results show that the hybrid approach, total cost reduced by 1.59% as compared to MRPSO, and 0.04% as compared to the FPA algorithm, respectively. Thus, it proved that hybrid apprach can attain the best solutions for minimum fuel cost as compared to past optimization methods.

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