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APPFPA based Best Compromised Solution for Dynamic Economic Emission Dispatch

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Abstract

In this paper a methodology is developed a to obtain Best Compromised Schedule (BCS) of Dynamic Economic Emission Dispatch (DEED) Problem. The DEED Problem is formulated to minimize both the fuel cost and Emission. The traditional weight method may not offer equal significance to both the Fuel Cost and Emission. The proposed methodology was a normalized objective function with a view of providing equal significance to both the objectives there by obtaining BCS. The solution methodology uses the recently suggested Adaptive Predator Prey Flower Pollination Algorithm (APPFPA) and is tested on various test system. The results on two tests system have clearly illustrated that the proposed method is better then weight method. The performance can be improved by combining the algorithms with out involving pareto-optimal solution set for the DEED problem.

Keywords: Adaptive Predator Prey Flower Pollination Algorithm, Dynamic Economic Dispatch, Dynamic Emission Dispatch, Normalized Objective Function Values, Proposed Method, Weight Method

1. Introduction

Optimal scheduling of thermal units, one of the most important functions in power system operation and planning, can lead to significant cost savings. The traditional solution techniques encounter difficulties such as getting trapped at local optima and increased computational complexity. Scarcity in energy resources, increasing power generation cost, ever-growing load demand and increasing concern over the environmental considerations for electric energy necessitate developing better DEED solution techniques. Though the Pareto front can be obtained either by solving the problem several times with different ω values or by using non-dominated sorting algorithms, the fuzzy based strategies may not extract the true BCS. The evolutionary search algorithms such as SA, GA, EP, PSO and ACO have been widely applied in solving DEcD problems[2]. The SA based approaches find the optimal solution using point-by-point iteration rather than a search over a population of individuals. Though they are simple to formulate besides requiring lower memory requirement than that of GA, they suffer from huge computational burden and end up with consuming exhaustively large execution time. But most of the GA based approaches involve binary representation of variables and the solution process involves complex search process. In this paper an Adaptive Predator Prey Flower Pollination Algorithm (APPFPA) for obtaining the BCS of DEED problem has been suggested. The method involving adaptive mutation scheme enhances the exploration and the exploitation capabilities of the search process and helps to land at the global best solution.

2. Flower Pollination Algorithm

The Flower Pollination Algorithm (FPA) is inspired by the pollination process of flowering plants. The objective of flower pollination is the survival of the fittest and the optimal reproduction of plants in terms of numbers

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as well as the fittest. FPA has been adopted through the following four steps:

Step 1: Global pollination represented in biotic and cross-pollination processes, as pollen carrying pollinators fly following Lévy flight.
Step 2:Local pollination represented in abiotic and self-pollination as the process does not require any pollinators.
Step 3:Flower constancy which can be developed by insects, which is on a par with a reproduction probability that is proportional to the similarity of two flowers involved.
Step 4:The interaction of local and global pollination is controlled by a switch

Probability $p \in [0,1]$, lightly biased toward local pollination.

We also assume that each plant only has one flower, and each flower only produce one pollen gamete for simplicity. This simplicity means a solution x_i is equivalent to a flower and/or a pollen gamete. There are two key steps in this algorithm; they are global pollination and local pollination. In the global pollination step, flower pollens are carried by pollinators such as insects, and pollens can travel over a long distance because insects can often fly and move in a much longer range and can be represented by:

$$x_l^{t+1} = x_l^t + \gamma L(\lambda)(x_l^t - g^*) \tag{1}$$

where x_l^t is the pollen of flower-l at t-th iteration and g^* is the current best solution found among all solutions at the current generation. Here γ is a scaling factor controlling the step size. $L(\lambda)$ is the Lévy flights that represents the strength of the pollination.

$$L \approx \frac{\lambda \Gamma(\lambda) \sin(\pi\lambda/2)}{\pi} \frac{1}{s^{1+\lambda}}, \quad (s >> s_o > 0) \tag{2}$$

Here $\Gamma(\lambda)$ is the standard gamma function, and this distribution is valid for large steps $s > 0$. For the local pollination, both Step 2 and Step 3 can be represented as

$$x_l^{t+1} = x_l^t + \varepsilon(x_n^t - x_p^t) \tag{3}$$

where x_n^t and x_p^t are pollen from different flowers of the same plant species mimicking the flower constancy in a limited neighborhood. For a local random walk, x_n^t and x_p^t comes from the same species then ε is drawn from a uniform distribution as [0, 1].

The FPA steps are outlined below:

1. Choose the parameters population size, maximum number of iterations for termination, switch probability p, etc
2. Initialize a population of NF flowers with random solutions.
3. Evaluate the objective function of each flower in the population.
4. Find/Update the current best solution.
5. For each flower in the population, generate a random number in a range of (0,1). If this random number is less than the p, perform local pollination, else do global pollination using Lévy flight.
6. Outputs the best solution, if the termination criteria are met, else go to step (3).
7. Stop.

2.1 Adaptive Mutation

The adaptive mutation rate can be heuristically evaluated from the diversity measure $D(t)$ of the population at generation-t as

$$P_m(t+1) = P_m^0 \cdot \left(1 + \frac{D(1) - D(t)}{D(1)}\right) \tag{4}$$

where

$$D(t) = \frac{1}{nf \cdot \chi} \cdot \sum_{i=1}^{nf} \sqrt{\sum_{j=1}^{nd} \left(x_{ij} - \bar{x}_j\right)^2} \tag{5}$$

$$\bar{x}_j = \frac{1}{nf} \cdot \sum_{i=1}^{nf} x_{ij} \tag{6}$$

2.2 Predator-prey Model

The property of predators helps the preys to explore search area more effectively. The predators are modeled based on the worst solutions as

$$x_{predator}(t) = x_{worst}(t) + \rho \cdot \left(1 - \frac{t}{Iter^{\max}}\right) \tag{7}$$

The fugue of prey can be modeled through maintaining distance between predator and prey as

$$\begin{aligned} x(t+1) &= x(t) + \rho \cdot e^{-|d|}, \quad if\ d > 0 \\ x(t+1) &= x(t) - \rho \cdot e^{-|d|}, \quad if\ d < 0 \end{aligned} \tag{8}$$

The algorithmic steps of the APPFPA are outlined below:

1. Choose the parameters population size, maximum number of iterations for termination, switch probability *p*, etc
2. Initialize a population of *NF* flowers with random solutions.
3. Evaluate the objective function of each flower in the population.
4. Find/Update the current best solution.
5. Evaluate the population diversity using Eq. (5).
6. Compute mutation rate using Eq. (4)
7. Perform the following for each flower in the population.

   a. Generate a random number in a range of (0,1). If this random number is less than the *p*, perform local pollination, else do global pollination using Levy flight.
   b. Probabilistically hunt the solutions using Eqs. (7) and (8)
   c. Probabilistically perform mutation based on the mutation rate.

8. Output the best solution, if the termination criterion is met, else goes to step (3).
9. Stop.

3. Problem Formulation

A suitable objective function that gives equal significance to both the fuel cost and emission components with a view to overcome the drawbacks of the existing approaches is developed by modifying the bi-objective function of Eq. (10) through normalizing the fuel cost and emission components as

$$Min \quad \Phi^M = \omega \left[\frac{\sum_{t=1}^{nt}\sum_{i=1}^{ng} F_i(P_{Git}) - F^{\min}}{F^{\max} - F^{\min}} \right] + (1-\omega) \left[\frac{\sum_{t=1}^{nt}\sum_{i=1}^{ng} E_i(P_{Git}) - E^{\min}}{E^{\max} - E^{\min}} \right] \tag{9}$$

Eq. (9) requires the values for $F^{\min}$, $F^{\max}$, $E^{\min}$, and $E^{\min}$, which can however be obtained through the following objective function of Eq (10) and (11).

$$F_i\left(P_{Git}\right) = a_i P_{Git}^2 + b_i P_{Git} + c_i + \left| d_i \sin\left\{ e_i (P_{Gi}^{\min} - P_{Git}) \right\} \right| \tag{10}$$

$$E_i(P_{Git}) = \alpha_i P_{Git}{}^2 + \beta_i P_{Git} + \gamma_i + \xi_i \exp(\delta_i P_{Git}) \tag{11}$$

for DEcD and DEmD respectively. The constrained optimization problem of Eq. (1) along with power balance constraint.

3.1 Demand-supply Balance

During each subinterval t, the total power generation must cover the total demand P_{Dt}, and the power loss P_{Lt} in transmission lines, namely,

$$\sum_{i=1}^{ng} P_{Git} - P_{Dt} - P_{Lt} = 0 \qquad t \in nt \tag{12}$$

where the transmission losses P_{Lt} is usually determined by Kron's loss function

$$p_{L,t} = \sum_{j=1}^{N}\sum_{j=1}^{N} p_{j,t} B_{Git} p_{j,t} + \sum_{j=1}^{N} B_{o,j} P_{j,t} + B_{o,o} \tag{13}$$

where B_{ij} is the (i, j) -th element of the loss coefficient square matrix of size n_g, B_{ok} is the *k*-th element of the loss coefficient vector, and B_{00} is the loss coefficient constant.

3.2 Real Power Balance Limit

For stable operation, the power output of each generator is bounded by the lower and the upper limits as follows:

$$P_{Gi}^{\min} \le P_{Git} \le P_{Gi}^{\max} \qquad i \in n_g, t \in nt \tag{14}$$

3.3 Generator Ramp Rate Limits

To avoid undue thermal stresses on the boiler and the combustion equipments, the actual operating range of each generator is restricted by its corresponding ramp rate limits. The ramp-up and ramp-down constraints for each generator can be written as follows:

$$\begin{aligned} &P_{Git} - P_{Git-1} \le UR_i \quad i \in n_g \quad t = 2,\cdots,nt \\ &P_{Git-1} - P_{Git} \le DR_i \quad i \in n_g \quad t = 2,\cdots,nt \end{aligned} \tag{15}$$

4. Proposed Method

The aim of this section is to explain to develop an APPFPA based solution method, which is capable of offering BCS for DEED with valve-point effects. In the existing solution approaches involving evolutionary algorithms, the ramp rate constraints are added to the objective function, which makes the solution process to converge very slowly. A new repair mechanism is introduced to handle ramp-rate constraints with a view to enhance the convergence of the algorithm. The solution process involves representation of problem variables and formation of a fitness function. Considering the P_G as the problem variables, the pollen of each flower can be represented by a real number matrix as shown in Figure 1. The variable P_{Git} represents real power generation of unit-i at interval- t.

The APPFPA searches for optimal solution by minimising a cost function similar to other stochastic optimization techniques. Based on this measure, the algorithm adjusts the control variables towards the optimum point.

The cost function can be obtained from the problem objective and constraint equations. The pollen of each flower during the solution process can be limited to satisfy the generation limit constraint of Eq. (13) but the power balance constraint of Eq. (11) is handled through penalty function approach. The augmented cost function ψ can be obtained by transforming the objective function Eq. (9) and power balance constraint Eq. (11) as

$$\text{Minimize } \Psi = K_1\,\Phi_{FE}{}^{M} + K_2 \sum_{t=1}^{ni} \left\{ \sum_{i=1}^{ng} P_{Git} - P_{Dt} - P_{Lt} \right\}^2 \quad (16)$$

Ramp rate limits are important constraints in Dynamic Economic Emission Dispatch (DEED) problem. During iterative process, pollen of each flower may violate these constraints and represent an infeasible solution. A repair algorithm that converts an infeasible solution into a feasible one can enhance the convergence of the solution process. The proposed repair algorithm is outlined below.

1. If ramp rate constraint, given by Eq. (14) of any generator- i at interval- t violates, replace it by randomly generating a value in between the permissible (P_{Git}–DR) and (P_{Git}+UR) limits.
2. Repeat step-1 till the ramp rate constraints of all the generators over the scheduling period are satisfied.

	1	2	3	4		ni
1	$P_{G\,1,1}$	$P_{G\,1,2}$	$P_{G\,1,3}$	$P_{G\,1,4}$	…	$P_{G\,1,ni}$
2	$P_{G\,2,1}$	$P_{G\,2,2}$	$P_{G\,2,3}$	$P_{G\,2,4}$	…	$P_{G\,2,ni}$
⋮		⋮		⋮		⋮
n_g	$P_{G\,ng,1}$	$P_{G\,ng,2}$	$P_{Gng,3}$	$P_{Gng,4}$	…	$P_{Gng,ni}$

Figure 1. Representation of pollen of each flower.

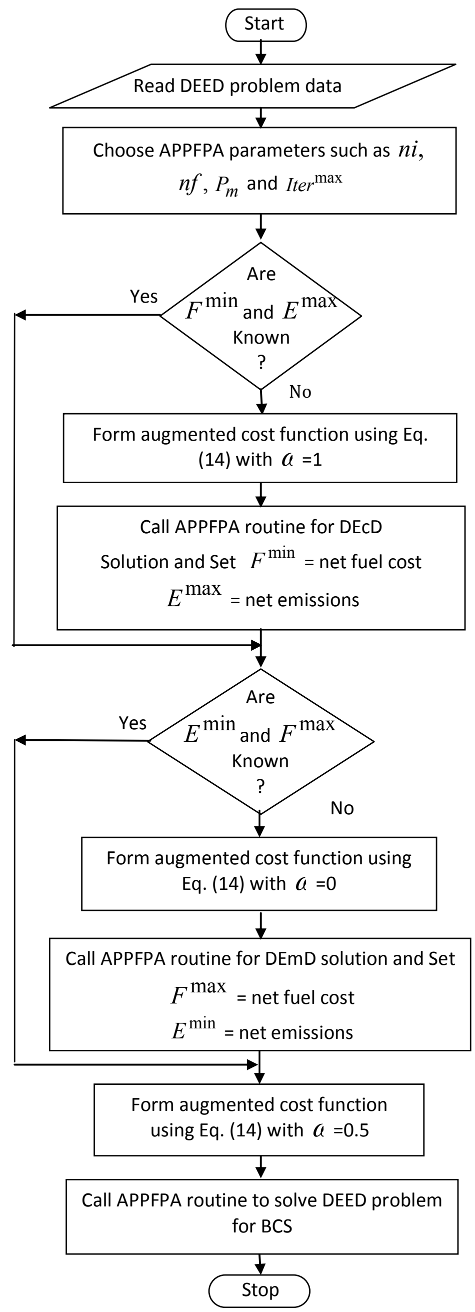

Figure 2. Flow chart of the Proposed Method.

The process of generating a new set of flowers from the randomly generated initial population through global and local pollination, predator-prey hunting and mutation may be called iteration. The iterations may be continued by taking the population obtained in the previous iteration as the initial population for next iteration. The flower having the best cost function value is stored along with its objective function at each iteration. The APPFPA iterative process of generating new population can be terminated after a fixed number of iterations. The flow of the proposed method for DEED is shown in Figure 3.

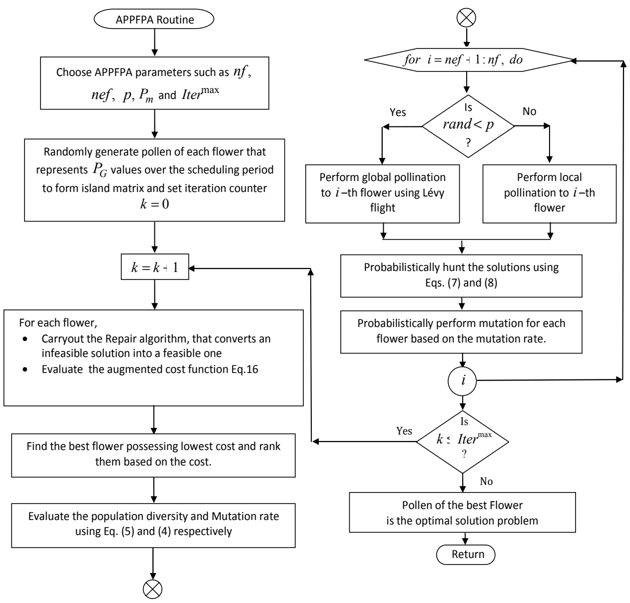

Figure 3. Flowchart of the APPFPA Routine.

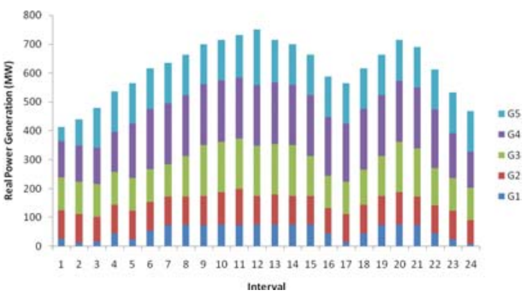

Figure 4. Real Power Generations of PM for Test Case-1.

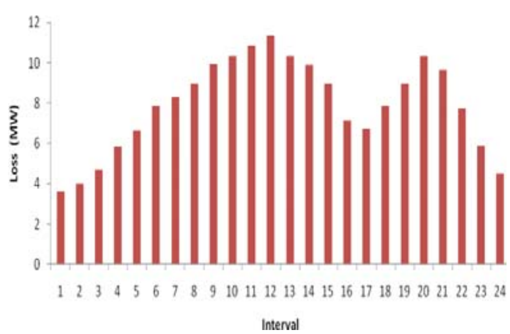

Figure 5. Network Loss at each interval of PM for Test Case-1

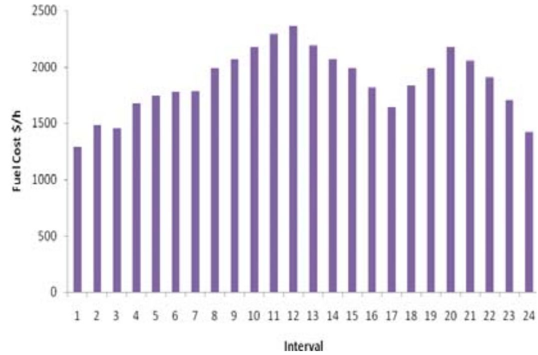

Figure 6. Fuel Cost and Emissions at each interval by PM for Test Case-1.

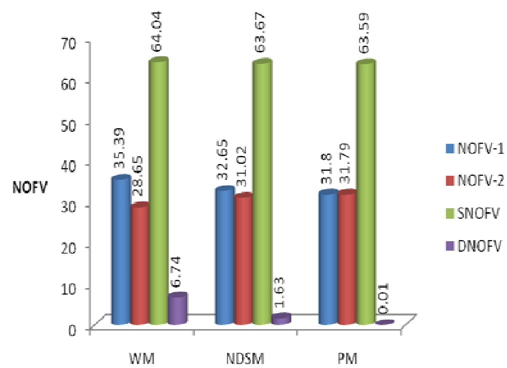

Figure 7. Comparison of NOFVs of PM for Test Case-1. WM- Weight method, NDSM- Non-dominated sorting method, PM- Proposed Method

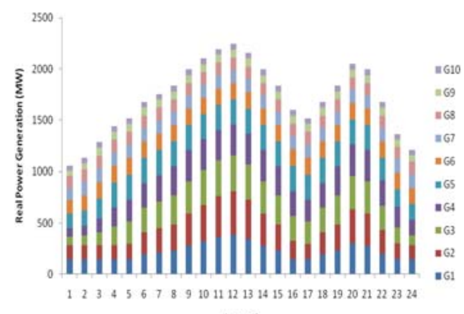

Figure 8. Real Power Generations of PM for Test Case-2

5. Simulation Results

The PM is tested on two different test cases with varying degree of complexity for studying its performance. The first one possesses 5 generating[3] a unit; the second system

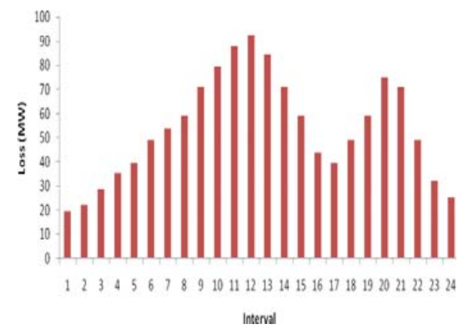

Figure 9. Network Loss at each interval of PM for Test-2

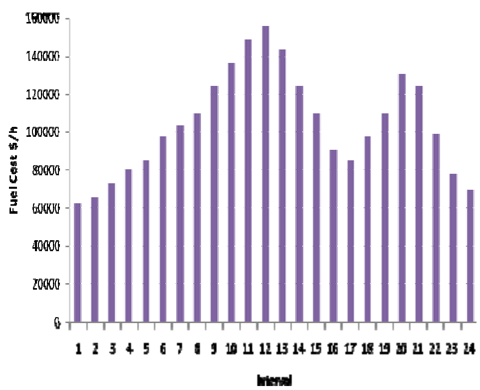

Figure 10. Fuel Cost for Test Case-2.

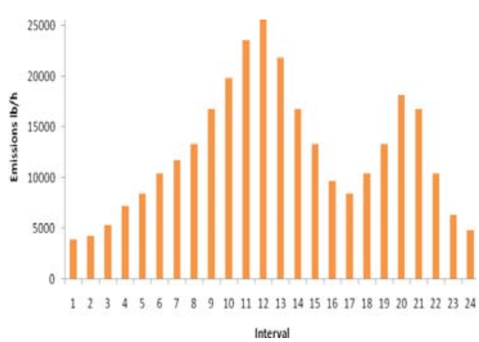

Figure 11. Emissions for Test Case-2.

comprises 10 generators[3]. The software package for PM is developed in Matlab platform and executed in a 2.3 GHz Pentium-IV personal computer. There is no guarantee that different executions of the developed design programs converge to the same design due to the stochastic nature of the FPA, and hence the PM is applied to these test systems for 30 independent trials (1000 iterations per trial) with the selected parameters and the best ones are presented. Results are also obtaining using weight method and non-dominated sorting method with a view of showing the superiority of the proposed method. The results obtained by the PMs for these test systems are compared with a few of the recent techniques available in the literature in the following sub-sections and discussed.

5.1 Test Case-1

The first system comprises 5 thermal units and the scheduling period is 24 hours, and losses are considered. In this case, valve loading effects and ramp-rate limits that result in a multi-minima solution space are considered. The fuel cost coefficients including valve-point effects, generation limits and ramp rate limits power demand data and B-loss coefficients are taken from [19]. The loss coefficients are assumed to remain unchanged over the scheduling period. The best fuel cost along with the mean and worst values of the PM for this test case-1 are compared with those of the methods outlined in Table 1. It is observed from these results that the PM offers a fuel cost of **44903.88** $/h$ and emissions of **18953.38** kg/h compared to other methods. The average generation cost over thirty solution runs are also compared with those of the existing approaches in Table 1. It is very clear from the table that the average value of the PM is much lower than other methods, indicating that the PM is more robust in obtaining the optimal solution.

5.2 Test Case-2

The second test system is one of the benchmark DEcD test systems derived from[3] and comprises ten generating units with a peak demand of 2150 MW. The fuel cost coefficients including valve-point effects, generation limits and ramp rate limits, power demand data and B-loss coefficient are taken from[3].

Table 1. Comparison of Results of PM for Test Case-1

	W=0.5		NOFV-1	NOFV-2
	Fuel Cost [$/$h$]	Emission [Kg/h]	Fuel Cost	Emission
Weight method	46195.74	18542.03	34.83	12.03
Non-dominated sorting method	44910.97	18954.91	20.61	19.38
PM	44903.88	18953.38	20.53	19.35

Table 2. Comparison of Results of PM for Test Case-2

	DEED		NOFV-1	NOFV-2
	Fuel Cost × 10^6[$/h]	Emissions × 10^5[Kg/h]		
NSGA [13]	2.5226	3.0994	–	–
WM [17]	2.5251	3.1246	–	–
MAMODE [15]	2.514113	3.02742	–	–
IBFA[16]	2.517116	2.99036	–	–
NSGA-II [13]	2.5226	3.0994	–	–
RCGA [13]	2.5251	3.1246	–	–
Weight method	2.510020167	3.011571061	35.3918	28.6510
Non-dominated sorting method	2.506596316	3.019168144	32.6446	31.0184
PM	2.505549142	3.021656575	31.8044	31.7939

The best fuel cost along with the mean and worst values of the APPFPA for this test case-1 are compared with those of the methods outlined in Table 2. It is observed from the results that the APPFPA offers the lowest fuel cost of $2.506596316{\times}10^6$ $\$/h$ compared to other methods. The average generation cost over thirty solution runs are also compared with those of the existing approaches in Table 1. It is very clear from the table that the average value of the APPFPA is much lower than other methods, indicating that the APPFPA is more robust in obtaining the optimal solution.

6. Conclusion

An intelligent algorithm involving APPFPA for finding the BCS of DEED problem has been explained in this chapter. A modified objective function has been developed to give equal significance to both the fuel cost and emission cost components. It has been found that the proposed strategy requires minimum solution runs to obtain the BCS unlike other strategies involving more number of solution runs. The results on four test cases have been found to demonstrate the effectiveness of the algorithm. This formulation exploits the capability of APPFPA and will culminate itself as a powerful tool in solving the DEED problem.

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