Mehran University Research Journal of Engineering and Technology
Vol. 40, No. 2, 371 - 382, April 2021
p-ISSN: 0254-7821, e-ISSN: 2413-7219
DOI: 10.22581/muet1982.2102.11

A Hybrid Flower Pollination Algorithm with Sequential Quadratic Programming Technique for Solving Dynamic Combined Economic Emission Dispatch Problem

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RECEIVED ON 11.03.2019, ACCEPTED ON 03.03.2020

ABSTRACT

This paper presents the solution of highly complex, non-linear, multi-objective Dynamic Combined Economic Emission Dispatch (DCEED) problem. DCEED is a power system optimization problem with conflicting objectives of fuel cost and emission. DCEED includes constraints like valve point loading effect, Transmission Losses and Ramp Rate limits. Solution of DCEED problem is given by a novel Hybridized Flower Pollination Algorithm (FPA) with Sequential Quadratic Programming (SQP). FPA is a nature inspired population based meta-heuristic optimization technique that models its search on the flower pollination process. The non-convex nature of generation because of numerous operational, physical and dynamic constraints, makes search space highly multi model and complex. This makes DCEED a challenging as well as an attractive problem for research. The effectiveness of FPA-SQP is tested and validated by applying it on IEEE Standard 5-unit and 10-unit non-convex test system in MATLAB environment for the time interval of 24 hours. The results achieved by this algorithm show significant reduction in cost and emission as compared to other available techniques in the literature.

Keywords: Flower Pollination Algorithm, Sequential Quadratic Programming, Emission Dispatch, Dynamic Combined Economic Emission Dispatch.

1. INTRODUCTION

For a developing country like Pakistan, Turkey, China *etc*. The importance of economics cannot be over emphasized. Pakistan's power industry is currently in a very serious downfall with severe power shortage and no hope to recover from this deficit soon. No matter how dire the situation maybe it still presents opportunity for smart minds in power system operation to devise strategies to schedule power system of country such that it requires minimum cost for operation. Allocating optimum power to a generating unit with the objective to minimize fuel cost while observing constraints is termed as Economic Dispatch (ED) [1, 2] problem. If this allocation of power is limited to a single fixed demand it is termed as static ED and if this power scheduling is done on a 24 hour time window it is termed as dynamic ED [3]. Many researchers have worked on ED and its variants achieving minimized costs, saving millions of dollars per year. But only minimization of fuel cost is not enough to achieve a sustainable and long-term solution for a heavily fossil fuel reliant power industry like Pakistan. Pakistan has been listed among top 10 countries most affected by climate change. The lack of choice in resources and the associated time in developing new clean sources makes it inevitable to use fossil fuel-based energy

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system but along comes all the environmental issues associated with it. Pollutants like CO_2, SO_2 and NO_x are discharged into the environment due to burning of fossil fuels like furnace oil [4]. These pollutants affect humans as well as many other life-forms which include animals, fish, birds and plants. They are also reported to causes damage to the materials, reducing visibility and cause global warming. Therefore a strategy is needed to protect the environment while overcoming the electricity crisis and to create sufficient and safe electricity, not only at the lowest cost but also at low level of pollution [5].

Reduction in emission can be achieved by shifting the load of the industry on a more environment friendly emission less energy resources [6] but their development requires the luxury of time which we do not have on our hands. Other alternative to reduce emission is by using equipment that funnels out pollutants from the exhaust of fossil fuel plants not allowing them to get dispersed in environment [7]. These options although less time intensive, requires investment that is not beneficial to energy producer but may even appear to them as a penalty. To achieve emission reduction while not straining energy producers, only feasible option is to perform emission dispatch. Emission Dispatch (EmD) is done by scheduling of generator units with the considerations of minimizing emission. EmD has many forms is literature depending on the nature of objective expression used and constraints considered. First form of EmD expresses fuel cost as objective function and considers emission as a constraint [8] but this setting between fuel cost and emission leads to complexity in achieving trade-off between them [9]. Second form of EmD considers fuel cost and emission as a single objective expression with unified constraints [10, 11] but this unification inhibits us to focus and target on fuel cost or emission individually. Third form of EmD considers emission and fuel cost as two different objective functions tied together in a single multi objective expression by assigning weights to each objective [12]. This setting allows flexibility in solution as well as individual autonomy and because of these strengths we use this form in our research.

A lot of mathematical techniques have been reported in literature to solve power system optimization problems. ED problem has been the talk of many research ventures since many decades. Initial attempts *made at the solution of ED problem included classical approaches like Lagrange relaxation method [13], linear programming, non-linear programming, integer programming [14], dynamic programming [15], direct search method [16] and Quadratic programming [17]. These initial attempts showed encouraging results, but more realistic non-convex complex problems proved to be too much of a task for these approaches. Classical approaches were dominantly dependent on selection of initial point and tended to get stuck in local optima's therefore as systems became more complex, they were unable to provide remarkable results. Another classical deterministic technique, Dynamic Programming showed better results when solving non-convex problems but it suffered from the curse of dimensionality [18]. To deal with these complexities' researchers created more optimization techniques that were free of the bounds of initial point selection and had complex procedure either nature inspired, based on some specie or a physical law that propelled a solution set from initial feasible point to an optimum point in the allotted search space. These techniques are broadly categorized as evolutionary, nature inspired meta-heuristic or stochastic approaches and some of these famous techniques or their variants include, Differential Evolution (DE) [19], Particle Swarm Optimization (PSO) [20-22], Artificial Immune System (AIS) [23], Hopfield neural network [24], Genetic Algorithm (GA) [25], evolutionary programming [26], Tabu search algorithm [27], self-organizing migrating algorithm [28], and cuckoo search algorithm [29, 30], Modified Artificial Bee Colony Optimization (MABC) [31], Non-Sorting Genetic Algorithm (NSGA) [32], Improved Bacterial Foraging Algorithm (IBFA) [33], Bee Colony Optimization with Sequential Quadratic Programming (BCO-SQP) [34], Differential Evolution with Sequential Quadratic Programming (DE-SQP), Particle Swarm Optimization with Sequential Quadratic Programming (PSO-SQP) [4] *etc.*

DCEED problem has also been attempted by some of these techniques or their variants. In Elaiw *et al.* [4] solved non-convex DCEED problem having valve point effect by two hybridized algorithms i.e. DE-SQP and PSO-SQP. Two different test systems were simulated, and the results achieved showed great potential for hybridization of optimization techniques with SQP. Taking inspiration from this work we have proposed a hybrid FPA-SQP technique to solve the non-convex DCEED problem having valve point effect.

2. MATHEMATICAL FORMULATION

This section presents the mathematical formulation and constraints expressions involved in DCEED problem.

2.1 Fuel Cost Function

The cost expression of a thermal unit over T time horizon can be approximated by a quadratic equation as shown in equation (1).

$$C_{Total} = \sum_{t=1}^{T} C_T = \sum_{t=1}^{T}\sum_{j=1}^{N} a_j P_j^2 + b_j P_j + c_j \qquad (1)$$

where j is the number of committed generator units, C_t is cost of generation at t time interval, N is total number of generating units, P_j is scheduled power for j^{th}unit and a, b, c are fuel cost coefficients.

Equation (1) is a reasonable approximation in order to obtain initial solution but when practical constraints like valve point effect of thermal units are considered then equation (1) cannot completely explain the non-convexity and multi-modal behavior by simple quadratic cost expression. The valve point effect creates non-linearity in the smooth cost curve of thermal generators making it bumpy and multi modal. This non-convex behavior can be expressed by augmenting the equation (1) with a sinusoidal expression as shown in Equation (2).

$$C_{Total} = \sum_{t=1}^{T}\sum_{j=1}^{N} a_j\, P_j{}^2 + b_j P_j + c_j + \left|e_j \sin(f_j(P_{j,min} - P_j))\right| \qquad (2)$$

(2)

where e, f are additional fuel co-efficient due to rippling effect and $P_{j,min}$ is the lower bound of j^{th} unit.

2.2 Emission Function

CO_2, SO_2 and NO_x are the major emissions of a conventional fossil fuel fired power plant. The emission of $CO_2, SO_2$is expressed by using quadratic equation where as NO_x is expressed by using exponential equation. The total emission over a time period T can be modeled as shown in Equation (3).

$$E_{Total} = \sum_{t=1}^{T} E_t = \sum_{t=1}^{T}\sum_{j=1}^{N} \alpha_j + \beta_j P_j + \gamma_j P_j^2 + \eta_j e^{\lambda_j P_j} \qquad (3)$$

where E_t is the emission at t time interval,$\alpha, \beta, \gamma, \eta$ and λ are pollutant coefficients, N is total number of generating units and $P_j$is scheduled power for j^{th} unit.

2.3 Objective Function

DCEED is multi-objective power system optimization problem with the final goal to achieve minimized fuel cost and emission at a particular-level of demand on a specified time horizon such that no operational or physical constraint is violated. The minimization of total fuel cost and emission are self-competing objectives which causes increase in the result of one as other is minimized. To overcome this obstacle and create a unified minimization expression we assign weights to each objective by defining a weighting factor “w” resulting in an expression shown in Equation (4).

$$\min \mathrm{Obj} = \min\{wC + (1 - w)E\} \qquad (4)$$

where C is non-convex, cost function and E is non-linear emission function, w is a weighting factor whose value may be selected by system operator in therange 0-1 depending upon regulatory requirements or user preferences. Changing the value of w will lead to different solutions. Selecting$w = 0$, will minimize emissions only, while increasing w, will increase emissions and will reduce cost, and setting $w = 1$ will optimize cost only. Summation of weight factors of each objective function will be equal to one. Addition of constraints to multi-objective DCEED problem makes non-convex, non-linear and computationally intensive.

2.4 Constraints

Unit Bounds Constraints: Scheduling of committed machines must be within their upper and lower bounds

$$P_{j,min} \leq P_j \leq P_{j,max} \text{for} j = 1,2,3, \ldots, N \quad (5)$$

where P_j is the active power output of j[th] machine and $P_{j,min}$ and $P_{j,max}$ are its upper and lower limits.

Power Balance Constraint: Output Power of all the machines must be equal to demand plus transmission losses.

$$\sum_{j=1}^{N} P_j - P_D - P_L = 0 \quad (6)$$

where P_D is demand, P_L represent transmission losses incurred at the specified level of generation.

Transmission losses can be determined through load flow or by application of quadratic Kron's formula.

$$P_L = \sum_{i=1}^{N}\sum_{j=1}^{N} B_{ij} P_i P_j + \sum_{i=1}^{N} B_{oi} P_i + B_{00} \quad (7)$$

Ramp Rate Constraint: Ramp rate is defined as power response capability of on-line generating units in terms of accommodating power changes in specified time intervals. Operating range of all the generating units is limited by ramp rate.

$$\begin{cases} DR = P_{j,min} \text{fort} = 1 \\ UR = P_{j,max} \text{fott} = 1 \\ P_{it} - P_{i(t-1)} \leq UR \text{fort} > 1 \\ P_{i(t-1)} - P_{it} \leq DR \text{fort} > 1 \end{cases} \quad (8)$$

3. PROPOSED HYBRID FLOWER POLLINATION ALGORITHM WITH SQP

3.1 Flower Pollination Algorithm

Population based meta-heuristic optimization techniques start their search by selecting a feasible non-optimum point randomly in search space and then propel this point to feasible optimum point through two distinct stages of search namely local and global search. These stages of search are governed by mathematical expressions that mimic either an animal's behavior in nature or a natural phenomenon. One such optimization technique that mimics the flower pollination process in nature is FPA that was proposed by Yang *et al.* [35]. FPA is a population-based optimization strategy that is based on principle of evolution. Like all population-based strategies FPA inherent the strengths of initial point independency and local optima avoidance. The two distinct phases of search as depicted by all population-based strategies also exist in FPA and they are termed as local and global pollination. FPA initially generates a random population of flowers which then evolve in each iteration through local and global pollination process until they reach optimum point. The global pollination process mimics biotic or cross pollination in which a pollinator disperses pollen to flower. This behavior can be expressed by Levy flight Equation (9) as:

$$x_i^{t+1} = x_i^t + L(g_* - x_i^t) \quad (9)$$

where x_i^t is the i-th flower at t-th iteration, L is the Levy constant and g_* is the current optimum.

Local pollination mimics abiotic or self-pollination process which does not require a pollinator and it is expressed as.

$$x_i^{t+1} = x_i^t + €\left(x_j^t - x_k^t\right) \quad (10)$$

where x_i^t, x_j^t, x_k^t are different flowers at t-th iteration and € is a constant randomly selected from normal distribution in range (0,1).

In order to control how much local or global pollination is performed a constant p is defined known as switch probability.

$$\begin{cases} \text{GlobalPollinationIfrand} < p \\ \text{LocalPollinationelse} \end{cases} \quad (11)$$

Another parameter includes flower constancy which indicates the reproduction probability for flower specie, and it is proportional to visit of pollinators to particular flower type but here for simplicity we have assumed single species of flowers.

Like all population-based approaches FPA shows remarkable strengths in local optimum avoidance but

FPA lacks in locating exact position of global optima. FPA like all population approaches can achieve near optimum convergence and requires additional assistance to enhance its tracking capabilities ensuring precision in locating global optimum. This enhancement is provided here by hybridizing it with SQP technique which is highly dependent of a strong starting point and has extraordinary local exploitation characteristics. In proposed strategy FPA provides its best solution to SQP as starting point, SQP than performs rigorous local space exploitation to locate global optimum. This strategy greatly enhances the shortcomings of FPA making it exceptional in tracking global optima with precision. Algorithm of proposed FPA-SQP is given below and Flow chart of the proposed technique is given in Fig. 1.

Algorithm:

1. **Initialization:** First, the population is randomly initialized in between upper and lower limit of all the generators, according to the following equation:
   $$\mathrm{Sol}(i,j) = P_{max}(j) - \left(P_{max}(j) - P_{min}(j)\right) \times \mathrm{rand}(0\sim 1)$$
2. **Calculate Fitness:** In this step we evaluate fitness of solution by calculating objective functions equation (4) and check for constraints violation.
3. **Create New Population by Local/Global Pollination:** The pollination type is selected by comparing a random number generated with probability switch pas depicted in equation (11). Depending on value of p we perform global pollination equation (9) or local pollination equation (10).
4. **Update Population:** In this step first, we check for constraint violation, then recalculate fitness for each flower and update the respective entries if new value is less than previous fitness value.
5. **Sort and Repeat:** The flower population is sorted in ascending order according to the fitness value and above steps from 2 to 4 are repeated till maximum iteration.
6. **Initializing SQP:** The best answer found from FPA is used as starting point to perform SQP.
7. **Stopping Criteria:** SQP refines answer until predefined number of decimal points or maximum iteration limit is reached.

The SQP sub-problem formulation is taken from [34,36] and a basic SQP problem solution process is shown in Fig. 2.

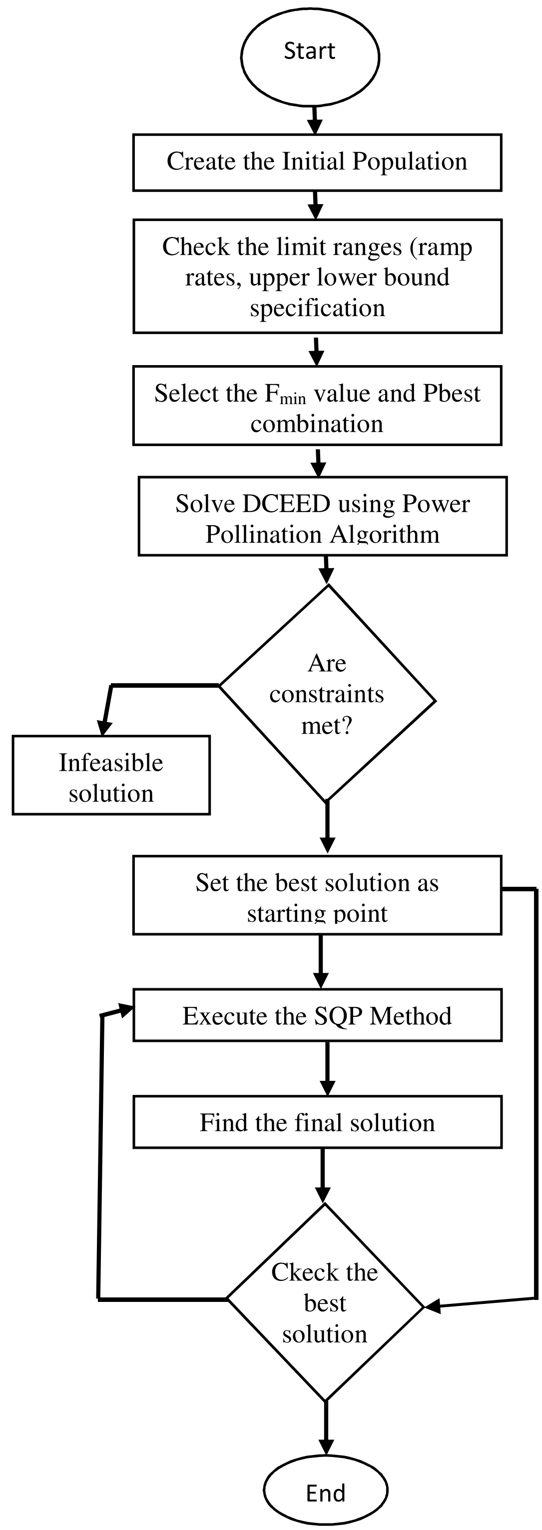

Fig. 1: Proposed Hybrid FPA-SQP Algorithm Flow Chart

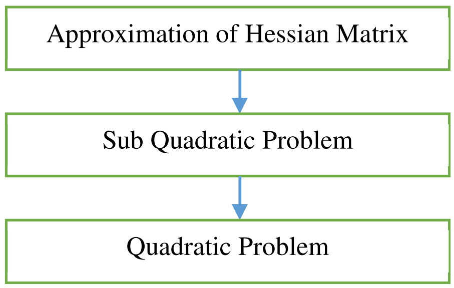

Fig. 2: Sequential Quadratic Programming Steps

The main objective is to model the minimized objective function through the SQP as a sub-problem.

$$\frac{1}{2}d_k^T H_k d_k + \nabla f(x_k)^T d_k \tag{12}$$

subject to:

$$[\nabla g(x_k)]^T d_k + g_i(x_k) = 0 \quad i = 1, \dots, m_e \tag{13}$$

$$[\nabla g(x_k)]^T d_k + g_i(x_k) \leq 0 \quad i = m_e + 1, \dots, m \tag{14}$$

where d_k is basis for the search direction.

The Lagrangian function is approximated by an approximate matrix in each iteration and then used to solve the SQP sub-problem.

Hessian matrix H_k of Lagrangian function defined by:

$$L(x, \lambda) = f(x) + \lambda^T g_i(x) at x = x_i \tag{15}$$

where f(x) represents objective function, g(x) constraints, H_k is approximated by B_k which is calculated from Quasi-Newton BFGS method,

$$B_{k+1} = B_k + \frac{q_k q_k^T}{q_k^T s_k} - \frac{(B_k s_k)(B_k s_k)^T}{s_k^T B_k s_k} \tag{16}$$

where;

$$s_k = x_{k+1} - x_k, \tag{17}$$

$$q_k = \nabla f(x_{k+1}) + \textstyle\sum_{i=1}^{m} \lambda_i \nabla g_i(x_k) - \nabla f(x_k) - \textstyle\sum_{i=1}^{m} \lambda_i \nabla g_i(x_k) \tag{18}$$

Here λ is Lagrange multiplier.

Solving SQP as a sub-problem gives d_k which is used to generate a new iteration given by equation (19):

$$x_{k+1} = x_k + \alpha_k d_k \tag{19}$$

The final augmented lagrangian function obtained by the combination of Lagrangian and Quadratic penalty method is:

$$L + f(x) - \sum_{i=1}^{m} \lambda_i (g_i(x) - s_i) + \frac{1}{2}\sum_{i=1}^{m} \rho_i (g_i(x) - s_i)^2 \tag{20}$$

where ρ is the penalty parameter and s are positive slack variable because of non-binding constraints.

4. SIMULATION RESULTS

The efficiency of proposed hybrid FPA-SQP technique was tested by implementing it on two standard test systems.

Test System 1: 5-unit non-convex taken from [4] including transmission loses and under constraints like generator limit, valve point effect and ramp rate.

Test System 2: 10-unit non-convex system taken from [36] including transmission losses and under constraints like generator limit, valve point effect and ramp rate.

Proposed technique is coded in MATLAB 13 environment. For each test system 30 distinct runs were performed by setting population size of flowers at 30 and total number of iterations 10000 iterations. The best trial solution for each case is depicted in Figs. 3-6.

4.1 Test System-1

FPA-SQP was applied to achieve different solutions of test system 1 taken from [4] by varying weighing factor in the range 0-1. The variation in weighing factor had significant impact on emission and cost. At a weighing factor value of 0we achieved best minimized emission but higher cost whereas at weighing factor value of 1 we encountered best minimum cost including significantly reduced emissions as compared to other techniques. At weighing factor value of 0.5 best compromise solution between cost and emissions was achieved. Table 1 shows real power assigned to each generator to achieve best compromise solution whereas Table 2 shows real power assigned to each generator to achieve best cost solution. The cost and emissions from each of these cases are shown in Figs. 3-4 respectively. Tables 3-4 show emission and cost comparison with other techniques available in literature respectively. The average computation time taken by FPA-SQP for solution of 5 unit test system was recorded to be 52.73 seconds.

Table 1: Optimal Dispatch of five-Unit Test System at Best Compromise Solution for 24-Hour Period

Optimal Dispatch of Five-Unit Test System at Best Compromise Solution for 24-hour Period											
Hour	P1	P2	P3	P4	P5	Hour	P1	P2	P3	P4	P5
1	22.658227	98.53947	112.6737	40	139.75979	13	44.553508	95	173.66165	232.82348	168.35948
2	37.942274	68.53947	152.6737	90	89.759786	14	74.553508	123.71272	133.66165	250	118.35948
3	63.740949	38.53947	112.6737	124.90792	139.75979	15	44.553508	93.712719	166.51796	200	158.11927
4	33.740949	20	152.6737	159.81524	169.56062	16	74.553508	123.71272	130.68568	150	108.11927
5	55.191343	20	175	194.72312	119.56062	17	52.168635	93.712719	170.68568	100	147.87904
6	71.857723	20	135	229.63093	159.32037	18	75	87.435715	130.68568	134.90799	187.63878
7	41.857723	38.514373	175	179.63093	199.08017	19	67.317946	117.43572	170.68568	169.81593	137.63878
8	71.857723	68.514373	158.89795	214.53897	149.08017	20	75	125	132.34402	204.72386	177.39851
9	44.553508	98.514373	118.89795	249.44688	188.83995	21	55.397889	95	172.34402	239.63179	127.39851
10	74.553508	125	158.89795	217.1557	138.83995	22	58.46491	65	132.34402	189.63179	167.1583
11	44.553508	95	162.80676	250	178.59967	23	68.560262	35	172.34402	139.63179	117.1583
12	74.553508	125	133.66165	200	218.35948	24	38.560262	49.952286	132.34402	89.631787	156.91808

Table 2: Optimal Dispatch of Five-Unit Test System at Best Minimum Cost Solution for 24-Hour Period

Optimal Dispatch of Five-Unit Test System at Best Minimum Cost Solution for 24-hour Period											
Hour	P1	P2	P3	P4	P5	Hour	P1	P2	P3	P4	P5
1	21.333255	20	112.67348	209.81582	50	13	31.940896	57.922056	165.30619	250	209.29174
2	51.333255	25.19794	152.67348	159.81582	50	14	37.850329	87.922056	125.30619	200	249.05154
3	40.188526	20	175	194.72375	50	15	30.678271	117.92206	165.30619	150	199.05154
4	70.188526	50	136.34332	229.63171	50	16	39.860294	87.922056	125.30619	184.90792	149.05154
5	75	80	175	179.63171	54.970801	17	22.560362	57.922056	165.30619	219.81585	99.05154
6	66.478151	110	175	214.53967	50	18	13.116849	87.922056	125.30619	250	139.75981
7	74.999997	124.99995	135.29982	249.44759	50	19	10.378067	57.922056	165.30619	250	179.5196
8	44.999997	94.999949	175	248.18529	100	20	32.135543	87.922056	175	200	219.27941
9	74.999997	124.99995	162.03399	198.18529	139.75978	21	32.817086	117.92206	135	234.90793	169.27941
10	75	101.34653	125.30619	233.09321	179.77243	22	45.506328	87.922056	175	184.90793	119.27941
11	45	117.92206	165.30619	183.09321	219.53216	23	45.820248	57.922056	135	134.90793	159.0392
12	61.139496	87.922056	125.30619	218.00112	259.29174	24	70.597755	27.922056	175	84.907928	109.0392

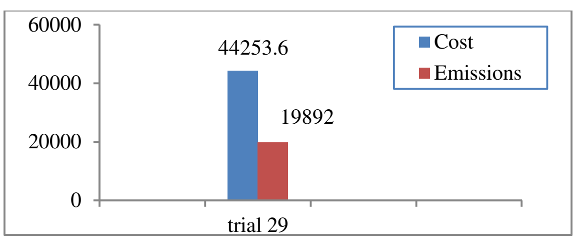

Fig. 3: Best Compromise Solution for Five-Unit Test System

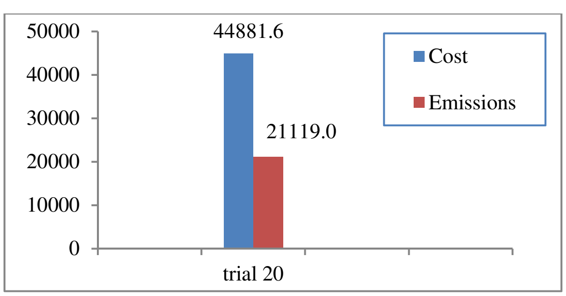

Fig. 4: Best Minimum Cost Solution for Five-Unit Test System

Table 3: Comparison of Five-Unit Test System with other Algorithms for Best Minimum Cost Solution

Best Minimum Cost Solution (w=1)		
Techniques	Cost ($)	Emissions (Lb)
DE-SQP [4]	43161	23080
PSO-SQP [4]	43263	23180
PSO [38]	47852	22405
SA [39]	48621	21,188
EP [39]	48,628	21,154
BA [40]	44,134.73	22362.22

Table 4: Comparison of Five-Unit Test System with other Algorithms for Best Compromise Solution

Best Compromise solution (w=0.5)		
Techniques	Cost ($)	Emissions (Lb)
DE-SQP [4]	44450	19616
PSO-SQP [4]	44542	19772
PSO [38]	50893	20163
PS [39]	47911	18927
BA [40]	45527.8	18384.51
FPA-SQP	44253.6	19892

4.2 Test System 2

Similarly test system 2 taken from [36] was solved by proposed FPA-SQP at different values of weighting factor. Solutions produced showed similar variation as observed for 5-unit system when weighing factor was changed. Tables 5-6 show the real power assigned to each of the ten generators to achieve best compromise solution and best cost solution respectively. The average computation time taken by FPA-SQP for solution of 10 unit test system was recorded to be 91.7 seconds.

Table 5: Optimal Dispatch of Ten-Unit Test System at Best Compromise Solution for 24-Hour Period

Optimal Dispatch of Ten-Unit Test System at Best Compromise Solution for 24-hour Period										
Hour	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10
1	150	135	93.1289	120.4065	122.8756	122.4499	129.5854	120	52.06351	10
2	150	135	73	119.6651	172.7331	137.8997	130	120	54.12057	40
3	150	135	112.681	169.6651	222.4661	153.3496	100	120	80	43.42122
4	150	135	189.285	188.5783	241.7777	160	130	120	80	46.84244
5	150	135	221.4841	230.9529	241.6445	160	130	120	80	50.26365
6	150	215	283.3907	241.3682	243	160	130	120	80	53.72492
7	150	215.6175	315.5903	285.9541	243	160	130	120	80	55
8	183.5138	222.8839	340	300	243	160	130	120	80	55
9	263.5138	302.8839	340	300	243	160	130	120	80	55
10	336.7623	336.8092	340	300	243	160	130	120	80	55
11	352.6014	413.2514	340	300	243	160	130	120	80	55
12	393.931	420.5173	340	300	243	160	130	120	80	55
13	331.5867	396.835	340	300	243	160	130	120	80	55
14	251.5867	316.835	338.1582	300	243	160	130	120	80	55
15	171.5867	236.835	338.0083	300	243	160	130	120	80	55
16	150	156.835	258.0083	250	237.7843	160	130	120	80	55
17	150	135	251.7725	200	237.6508	160	130	120	80	55
18	150	204.417	283.9722	250	243	160	130	120	80	55
19	184.1309	222.2665	340	300	243	160	130	120	80	55
20	264.1309	302.2665	340	300	243	160	130	120	80	55
21	257.0184	309.5327	340	300	243	160	130	120	80	55
22	177.0184	229.5327	260	250	243	160	130	120	80	27.20953
23	150	149.5327	180	200	214.2708	160	130	120	50	10
24	150	135	110.0115	150	164.2708	160	100	120	80	40

Table 6: Optimal Dispatch of Ten-Unit Test System at Best Minimum Cost Solution for 24-Hour Period

Optimal Dispatch of Ten-Unit Test System at Best Minimum Cost Solution for 24-hour Period										
Hour	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10
1	150	135	164.8349	60	73	160	129.5904	120	20	43.42092
2	150	135	188.3142	60	122.8666	160	99.5904	120	50	46.84207
3	150	135	235.8437	110	172.8666	160	106.1206	120	80	16.84207
4	150	135	258.0037	160	222.5995	160	112.6508	120	80	43.42146
5	150	135	290.1981	210	238.307	160	119.1809	120	50	46.83999
6	150	138.1325	340	260	243	160	130	120	80	55
7	192.0619	135	340	300	243	160	130	120	80	55
8	191.3961	215	340	300	243	160	130	120	80	55
9	271.3961	295	340	300	243	160	130	120	79.99999	54.99999
10	298.5537	375	340	300	243	160	130	120	80	55
11	371.8022	394.0629	340	300	243	160	130	120	80	55
12	368.4263	446.02	340	300	243	160	130	120	80	55
13	362.4321	366.02	340	300	243	160	130	120	80	55
14	282.4321	286.02	338.2709	300	242.8665	160	130	120	80	55
15	202.4321	206.02	338.2337	300	242.7332	160	130	120	80	55
16	150	135	335.3035	250	242.5997	160	100	120	50	55
17	150	135	255.3035	249.5176	242.4663	160	130	120	52.05703	25
18	150	135	315.0737	299.5176	243	160	130	120	80	43.42119
19	191.3961	215	340	300	243	160	130	120	80	55
20	271.3961	295	340	300	243	160	130	120	80	55
21	264.2811	302.2665	340	300	243	160	130	120	80	55
22	184.2811	222.2665	262.4979	250	242.8667	160	130	90	80	55
23	150	142.2665	182.4979	200	192.8667	111.4711	130	120	80	55
24	150	135	102.4979	150	216.8843	160	100	90	50	55

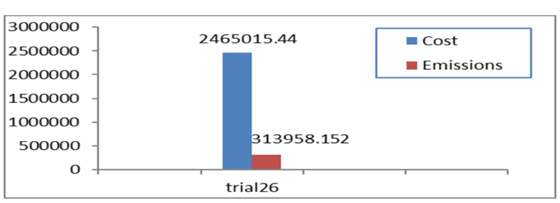

Fig. 5: Best Compromise Solution for Ten-Unit Test System

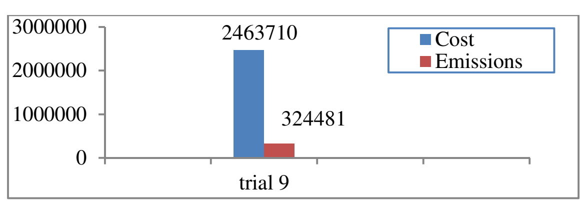

Fig. 6: Best Minimum Cost Solution For Ten-Unit Test System

Figs. 5-6 show cost and emissions for each of the above-mentioned dispatches respectively whereas Tables 7 and 8 show the comparison of cost and emission with other techniques available in literature for each of the best cost solution and best compromise solution respectively.

4.3 Discussion

Results for best cost solution shown in Table 3 for test system 1 shows that, the FPA-SQP was able to acquire an improvement in cost of 3746$, 3739$ and 2970$ as compared to EP [39], SA [39], PSO [38] respectively. As for DE-SQP [4], BA [40] and PSO-SQP [4] the proposed technique was able to minimize 1961 Lb, 1243.22 Lb and 2061 Lb of emissions respectively. Whereas, for best compromise solution of test system 1 shown in Table 4 the proposed technique was able to achieve an improvement in cost of 196.4$, 288.4$, 1274.2$, 6639.4$ and 3657.4$ as compared to DE-SQP [4], PSO-SQP [4], BA [40], PSO [38] and PS [39] respectively whereas the emission levels of each technique were also comparable. The transmission loses incurred in both cases were 193.003 and 190.056 MW respectively.

Similarly, for best cost solution shown for test system 2 shown in Table 7 the proposed technique was able to achieve an improvement in cost in range 10^6 of 0.1217$, 0.1085$, 0.05599$, 0.05309$, 0.01799$, 0.00219$, 0.00309$, 0.010763$, 0.018024$ and 0.053091$ as compared to EP [41], PSO [41], AIS [41], I-BFA [33], for DE-SQP [4], PSO-SQP [4], GCABC [42], IBFA [42] and NSGAII [42] respectively at a comparable emission level. Also, for best cost solution of test system 2 shown in Table 8 the proposed technique was able to acquire an improvement in cost in the range of 10^6 and emission in the range of 10^5, of 0.001785$ at 0.01682 Lb, 0.005085$ at 0.01112 Lb, 0.083902$ and 0.049409$ respectively as compared to DE-SQP [4], PSO-SQP [4], DE [43] and MDE [43]. The transmission losses incurred in both cases were 1286.93 and 1286.01 MW respectively.

The comparison with literature proves that effectiveness of FPA-SQP technique. Further to elaborate the transition of FPA-SQP between different phases of search convergence characteristics for 5 unit test system under a fixed hour for 1000 iterations is shown in Fig. 7. From figure it can be seen that FPA-SQP transitions smoothly among exploration and exploitation phases during its quest for optimal values. The slopes on the characteristic curves indicate exploration whereas the flat regions indicate exploitation.

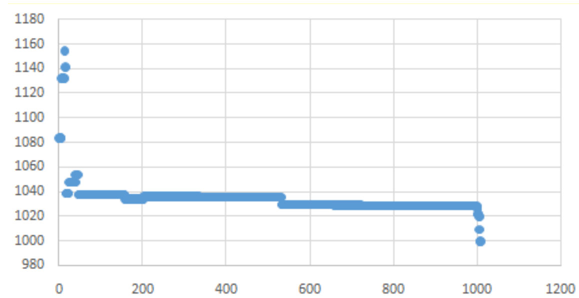

Fig. 7: Convergence Curve for 5 Unit System for a Fixed Hour

Table 7: Comparison of Ten-Unit Test System with other algorithms for best minimum cost solution

Best Minimum Cost Solution		
Technique	Cost*10^6 ($)	Emissions*10^5 (Lb)
EP [41]	2.5854	-
PSO [41]	2.5722	-
AIS [41]	2.5197	-
I-BFA [33]	2.4817	3.2750
DE-SQP [4]	2.4659	3.2405
PSO-SQP [4]	2.4668	3.3023
GCABC [42]	2.474472	2.93416
IBFA [42]	2.481733	2.95833
NSGAII [42]	2.5168	3.174
FPA-SQP	2.463709	3.24481

Table 8: Comparison of Ten-Unit Test System with other Algorithms for Best Compromise Solution

Best Compromise solution		
Technique	Cost*10^6 ($)	Emissions*10^5 (Lb)
DE-SQP [4]	2.4668	3.1564
PSO-SQP [4]	2.4701	3.1507
DE [43]	2.548917	3.084189
MDE [43]	2.514424	2.996616
FPA-SQP	2.465015	3.13958

5. CONCLUSION

In this study, a hybrid FPA with SQP was proposed to solve the DCEED problem under the effect of valve point and Ramp rate constraint including transmission losses. The proposed strategy utilizes FPA to initialize its search for optimum point and then refines its search by applying SQP. Hybrid FPA-SQP was implemented on IEEE standard 5-unit and 10-unit test system in MATLAB 13 environment. The results obtained indicate that FPA-SQP was able to achieve better solution both in terms of cost as well as emissions. The success of this approach is a motivating factor for future research, exploring more hybrid options and improvement in solution strategies.

ACKNOWLEDGEMENT

The authors wish to acknowledge the support from Ph.D. and MSc Research Scholars and also the faculty especially Dean and Chairman of Electrical Engineering Department, University of Engineering and Technology Taxila, Pakistan.

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