Optimal Location and Control Parameter Settings of UPFC using Differential Evolution Algorithm

R.Vanitha
Research Scholar
Sathyabama University, Chennai, India

M.Sudhakaran
Associate Professor, Pondicherry Engineering College, Pondicherry, India

ABSTRACT
The main objective of this paper is to find the optimal location and control parameters settings of Unified Power Flow Controller (UPFC) with regard to power loss minimization. The proposed algorithm is based on steady state power injection model of UPFC. In this paper, two Evolutionary optimization techniques, namely Differential Evolution Algorithm (DE) and Genetic Algorithm (GA) are employed to solve optimal power flow problems. IEEE 14 bus & IEEE 30 bus test power systems are used for studies. The obtained results indicate that both techniques can successfully find the optimal location and control parameter settings of UPFC, but DE is faster than GA from the time perspective.

Keywords
Optimal power flow, Power loss minimization, Genetic Algorithm, Differential Evolution, Evolutionary Optimization technique

1. INTRODUCTION
Optimal power flow (OPF) is a nonlinear programming problem (NLP) which is used to minimize a desired objective function subject to certain system constraints by determining the optimal control parameter settings. An optimization technique is used to determine the global optimum solution to a given OPF problem. Optimization means finding the best-suited solution for a problem within its given constraints and flexibilities.

Several conventional techniques like nonlinear programming (NLP), quadratic programming, mixed integer programming and Newton techniques are used to obtain the solution for optimal power flow problems [1, 2]. The limitations of these methods lead to the development of Evolutionary computing techniques like genetic algorithm (GA), simulated annealing (SA), particle swarm optimization (PSO), tabu search (TS), Differential Evolution algorithm (DE) and many more [3 – 11] . These algorithms can solve complex optimization problems which are non-linear, non- continuous, non –differentiable and multi- dimensional.

Differential Evolution (DE) algorithm is a stochastic population based search optimization algorithm. It has certain advantages like finding the true global minimum irrespective of initial parameter values. It uses few control parameters to find the true global minimum. It is similar to Genetic algorithm which uses mutation, crossover, and selection operators. It uses the mutation operation as a search mechanism and selection operation as a direction mechanism. It employs a greedy selection process which leads to faster convergence compared with Genetic algorithm [12].

In transmission systems, Flexible AC transmission systems (FACTS) increase system transmission capacity and provide flexibility in power flow control. [13, 14]. These FACTS devices are used to overcome regulatory problems in transmission systems. Unified Power Flow Controller (UPFC) is the most sophisticated FACTS device. It can independently or simultaneously controls the active power, the reactive power and the bus voltage to which it is connected [15].

Several steady state models are available for UPFC to be implemented in power flow program based on Newton- Raphson algorithm. Some are decoupled UPFC model, injection UPFC model and Comprehensive NR UPFC model. Each model has its own merits and demerits. A mathematical model for UPFC which will be referred as UPFC injection model is used in this study [16]. The advantage of this method is that it can be easily implemented in existing power flow program and UPFC can be adjusted to work as series compensator, voltage regulator, or phase shifter [17].

In this paper, Differential Evolution algorithm is used in OPF technique to determine the optimal location and control parameter settings of UPFC for minimization of total real power loss in the power system.

This paper is structured as follows. In section 2, Basic concepts of UPFC are introduced. In section 3, the problem for the study is formulated. Section 4 presents an overview of Differential Evolution algorithm. Section 5 discusses the results for DE and GA algorithms and its comparisons. Section 6 summaries the main ideas presented in this paper.

2. BASIC CONCEPTS OF UPFC

2.1 Operating Principle of UPFC
The Unified Power Flow Controller consists of two voltage sourced converters connected back-to- back through a common DC link provided by a DC storage capacitor. (Fig 1).

The primary function of converter 1 is to supply or absorb the real power demanded by converter 2 through the common DC link. Converter 1 can also generate or absorb controllable reactive power if it is desired and thereby provides independent shunt reactive compensation for the line. The main function of UPFC is performed by converter 2 by injecting an AC voltage with controllable magnitude and phase angle in series with the transmission line via a series transformer. The required reactive power is supplied or absorbed locally by converter 2 and active power is exchanged as a result of the series injection voltage.

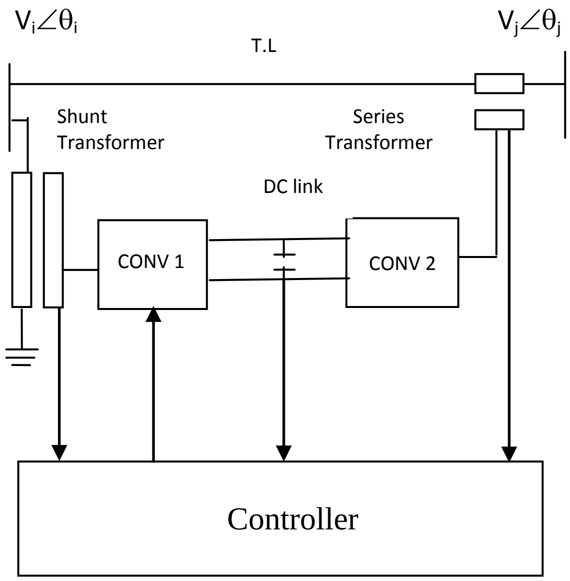

Fig 1 : UPFC Schematic Diagram

2.2 UPFC Steady State Injection Model

UPFC can be easily incorporated into the power flow equation using the steady state injection model [16] UPFC power injection model is presented in Fig. 2.

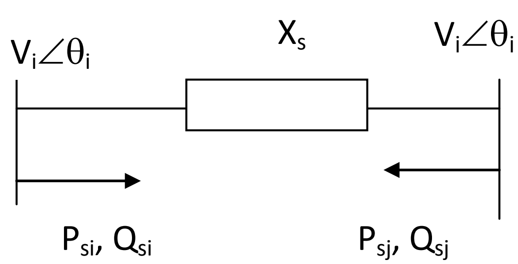

Fig 2: UPFC Model

$$P_{si} = rb_s V_i \ V_j \sin(\theta_{ij} + \gamma) \tag{1}$$

$$P_{sj} = -rb_s V_i V_j \sin(\theta_{ij} + \gamma) \tag{2}$$

$$Q_{si} = rb_s V_i^2 \cos\gamma \tag{3}$$

$$Q_{sj} = -rb_s V_i V_j \cos(\theta_{ij} + \gamma) \tag{4}$$

If a UPFC is located between node i and node j in a power system, the admittance matrix is modified by adding a reactance equivalent to Xs between the nodes i and j.The Jacobian matrix is modified by addition of appropriate powers.

3. PROBLEM FORMULATION

To achieve the best utilization of the existing transmission systems, UPFC device should be installed in such a place to minimize the total real power loss. In this paper the objective function chosen is minimization of total real power loss P_{loss} in power system under several loading conditions.

3.1 Objective Function

$$\min P_{loss} = \sum_{i=1}^{nl} G_{i,j} \left\{ V_i^2 + V_j^2 - 2V_i V_j \cos(\delta_i - \delta_j) \right\} \tag{5}$$

Where

P_{loss}	:	Active power loss function
G_{ij}	:	Conductance of line i - j
V_i	:	Voltage magnitude at bus i
V_j	:	Voltage magnitude at bus j
δ_i	:	Voltage angle at bus i
δj	:	Voltage angle at bus j
nl	:	Total number of transmission lines

3.2 System Constraints

3.2.1 Equality Constraint: Power flow equation

$$P_{Gi} = P_{Di} + \sum_{j=1}^{nb} |V_i||V_j||Y_{ij}| \cos(\theta_{ij} - \delta_i + \delta_j) \tag{6}$$

$$Q_{Gi} = Q_{Di} + \sum_{j=1}^{nb} |V_i||V_j||Y_{ij}| \sin(\theta_{ij} - \delta_i + \delta_j) \tag{7}$$

Where

P_{Gi}	:	real power generation at bus i
Q_{Gi}	:	reactive power generation at bus i
P_{Di}	:	real power demand at bus i
Q_{Di}	:	reactive power demand at bus i
θ_{ij}	:	angle of bus admittance element i, j
Y_{ij}	:	magnitude of bus admittance element i, j
nb	:	Total number of buses

3.2.2 Inequality Constraints

$$V_i^{\min} \le V_i \le V_i^{\max}$$

$$P_{Gi}^{\min} \le P_{Gi} \le P_{Gi}^{\max}$$

$$Q_{ci}^{\min} \le Q_{ci} \le Q_{ci}^{\max} \tag{8}$$

$$r_{\min} \le r \le r_{\max}$$

$$\gamma_{\min} \le \gamma \le \gamma_{\max}$$

Where

V_i^{min}, V_i^{max} : upper and lower limits of voltage magnitude at bus i

P_{Gi}^{min}, P_{Gi}^{max} : upper and lower limits of power generated by generator i.

Q_{ci}^{min}, Q_{ci}^{max} : upper and lower limits of reactive power source i.

r ,γ : UPFC parameters

4. OVERVIEW OF DIFFERENTIAL EVOLUTION ALGORITHM

In 1995, Storn and Price first proposed Differential Evolution (DE) algorithm [18]. DE is a new stochastic parallel direct search method used for Global Optimization. It has been widely studied and applied in many fields [19, 20, 21]. This algorithm uses a population P which consists of N individuals that evolve over G generations to reach an optimal solution. The number of the individual`s N in the population P remains constant during the minimization process. The dimension D of each individual will be equal to the number of decision or design parameters.

$$P = \left[Y_1^{(G)}, \ldots\ldots\ldots\ldots\ldots Y_N^{(G)}\right] \qquad (9)$$

$$Y_i^G = \left[X_{1i}^{(G)}, \ldots\ldots\ldots\ldots X_{Di}^{(G)}\right]^T \qquad (10)$$

Where

i : 1, 2 ……N

P : Population Vector

X : decision Variable

D : number of decision variable

G : number of Generation

N : Population size

Like other evolutionary algorithms, the initial population is chosen randomly and uniformly over the entire parameter space. The optimization process is carried out using the three basic operations like Mutation, Cross over and Selection for all individuals until a stopping criterion is met.

4.1 DE Algorithm

Initialization
Evaluation
Repeat
  Mutation
  Crossover
  Evaluation
  Selection
Until (termination criteria are met)

4.2 DE Optimization Process

4.2.1 Initialization

The first step in Differential Evolution algorithm is to create an initial population. Each decision or design parameter of each individual of population is assigned with a random value and that value must lie within the feasible bounds of the decision variable.

$$Y_{i,j}^{(0)} = Y_j^{\min} + \left(Y_j^{\max} - Y_j^{\min}\right) * rand[0,1] \qquad (11)$$

Where

i : 1,2 …….N

j : 1, 2 ……..D

Y_j^{min} , Y_j^{max} : Maximum and Minimum limit of j[th] decision Vector

4.2.2 Mutation

The mutation operator introduces new parameters into the population. For crossover and mutation several types of strategies are in use. The strategy which is implemented is explained in detail. The mutation operator derives the mutant vector Y_M by using the weighted difference of two randomly selected population vectors Y_b and Y_c and adds to another randomly selected population vector Y_a. All of these randomly selected vectors must be different from each other. The convergence is improved by scaling the difference vector by a user defined constant known as the scaling constant S in the range [0 - 1.2].

$$Y_M^{(G)} = Y_a^{(G)} + S\left(Y_b^{(G)} - Y_c^{(G)}\right) \qquad (12)$$

Where

Y_a, Y_b, Y_c : randomly chosen vectors from the population

Y_a, # Y_b # Y_c

S= Scaling factor [0 - 1.2]

4.2.3 Crossover

The crossover operator creates the trial vectors, which are used in the selection process. The mutant vector is mixed with target (parent) vector to yield trial vector by creating a random number using any one of the distributions like uniform distribution, binomial distribution or exponential distribution and compared against a user defined constant referred to as the crossover constant CR in the range [0 - 1]. If the value of the random number is less or equal than the value of the crossover constant, the parameter will come from the mutant vector, otherwise the parameter comes from the parent vector.

$$Y_T^{(G)} = \left\{ \begin{array}{c} Y_M^{(G)} if \eta_j \le CR or j = q \\ Y_{i,j}^{(G)}, otherwise \end{array} \right\} \qquad (13)$$

Where

q : randomly chosen index from {1, 2 …D}

$Y_{i,j}^{(G)}$: target Vector or Parent Vector

$Y_M^{(G)}$: mutant vector

$Y_T^{(G)}$: trial vector

CR : Crossover Constant [0 - 1]

4.2.4 Selection

The selection operator chooses the vectors that are going to be the population in next generation. Selection is the operation through which better offspring are generated. The fitness of the trial vector and the corresponding target vector is compared and better one will be selected by the operator.

$$Y_{i,j}^{(G+1)} = \begin{cases} Y_T^{(G)} iff \left(Y_T^{(G)}\right) \leq f\left(Y_{i,j}^{G}\right) \\ Y_{i,j}^{(G)}, otherwise \end{cases} \tag{14}$$

5. DE IMPLEMENTATION RESULTS

To verify the effectiveness and performance of the DE algorithm, IEEE 14 bus and IEEE 30 bus test power systems were used for test and compared with real coded Genetic algorithm [22, 23]. The algorithms are implemented in MATLAB 7.5 for different load conditions for determination of the optimal settings and location of UPFC to have minimum real power loss. Table 1 & 2 depicts the results of UPFC location, its optimal settings and total real and reactive power loss for IEEE 14 bus test system in DE & GA. Table 3 shows the comparison results of DE and GA in terms of real power loss, execution time in sec. Table 4 & 5 reveals the results of IEEE 30 bus test system in DE & GA and Table 6 compares the results of DE & GA. All the studies are carried out on a PC with Intel core i5 2.53 GHZ processor and 4GB RAM.

Optimal Parameter Settings

No. of Decision Variables : 2

Population size (N) : 30

Maximum Number of generations (G) : 50

Crossover Constant (CR) : 0.9

Scaling Factor (S) : 0.5

Table 1: Results of IEEE 14 –Bus System (Differential Evolution)

Cases		**Status 1 (Without UPFC)**	**Status 2 (With one UPFC)**	**Status 3 (With Two UPFC's)**
Normal loading	ΣPloss(MW) ΣQloss(MVAR) Location (Bus No – Bus No) UPFC Settings	13.3931 26.2597 - -	13.3119 26.3271 2-4 r = 0.067, γ=157.48°	13.2983 26.5089 2-4 & 2-5 r = 0.039, γ=338.84°
Twice normal loading	ΣPloss(MW) ΣQloss(MVAR) Location (Bus No – Bus No) UPFC Settings	70.859 256.378 - -	70.669 256.32 3-4 r = 0.04, γ=201.28°	70.581 257.71 2-4 & 3-4 r = 0.035, γ=268.50°
3 Times normal loading	ΣPloss(MW) ΣQloss(MVAR) Location (Bus No – Bus No) UPFC Settings	206.598 789.599 - -	205.93 789.49 3-4 r = 0.035, γ=244.78°	205.87 789.38 3 -4 & 10 – 11 r = 0.022, γ=47.80°
Active load increasing thrice at bus #4	ΣPloss(MW) ΣQloss(MVAR) Location (Bus No – Bus No) UPFC Settings	27.7635 77.4348 - -	27.5955 77.8550 2-4 r = 0.06, γ=217.82°	27.5302 78.128 2 -4 & 2- 5 r = 0.038, γ=14.11°
Active & Reactive load increasing thrice at bus #9	ΣPloss(MW) ΣQloss(MVAR) Location (Bus No – Bus No) UPFC Settings	22.7632 77.6845	22.6952 77.4250 5-6 r = 0.028, γ=167.67°	22.666 71.956 2 – 4 & 5 – 6 r = 0.028, γ=167.67°

Table 2: Results of IEEE 14 –Bus System (Genetic Algorithm)

Cases		**Status 1 (Without UPFC)**	**Status 2 (With one UPFC)**	**Status 3 (With Two UPFC's)**
Normal loading	ΣPloss(MW) ΣQloss(MVAR) Location (Bus No – Bus No) UPFC Settings	13.3931 26.2597 - -	13.3130 26.3312 2-4 r = 0.0667, γ=158.26°	13.2989 26.5117 2-4 & 2-5 r = 0.0389, γ=340.77°

Twice normal loading	ΣPloss(MW) ΣQloss(MVAR) Location (Bus No – Bus No) UPFC Settings	70.859 256.378 - -	70.672 256.33 3-4 r = 0.0395, γ=219.01°	70.583 257.72 2-4 & 3-4 r = 0.0333, γ=263.79°
3 Times normal loading	ΣPloss(MW) ΣQloss(MVAR) Location (Bus No – Bus No) UPFC Settings	206.598 789.599 - -	205.94 789.54 3-4 r = 0.0341, γ=225.52°	205.87 789.33 3 -4 & 10 – 11 r = 0.022, γ=44.42°
Active load increasing thrice at bus #4	ΣPloss(MW) ΣQloss(MVAR) Location (Bus No – Bus No) UPFC Settings	27.7635 77.4348 - -	27.5970 77.5099 2-4 r = 0.058, γ=173.15°	27.5302 78.1281 2 -4 & 2- 5 r = 0.0378, γ=12.669°
Active & Reactive load increasing thrice at bus #9	ΣPloss(MW) ΣQloss(MVAR) Location (Bus No – Bus No) UPFC Settings	22.7632 77.6845	22.6958 77.4034 5-6 r = 0.0271, γ=166.60°	22.6662 77.9666 2 – 4 & 5 – 6 r = 0.0276, γ=357.30°

Table 3: Comparison between Differential Evolution Algorithm & Genetic Algorithm (IEEE 14bus)

Case	**Decrease in real power loss Δ PL (KW)** **one UPFC**		**Decrease in real power loss Δ PL (KW)** **Two UPFC's**		**CPU Time (sec)** **Two UPFC's**	
	DE	**GA**	**DE**	**GA**	**DE**	**GA**
Normal loading	81.2	80.1	94.8	94.2	3.73	22.2
Twice normal loading	191	187	278	276	5.01	51.4
3 Times normal loading	668	658	728	728	4.84	50.6
Active load increasing thrice at bus #4	168	167	233.3	202.3	5.49	51.4
Active & Reactive load increasing thrice at bus #9	68	67.4	97.2	97	5.05	55.7

Table 4: Results of IEEE 30 –Bus System (Differential Evolution)

Cases		**Status 1 (Without UPFC)**	**Status 2 (With one UPFC)**	**Status 3 (With Two UPFC's)**
Normal loading	ΣPloss(MW) ΣQloss(MVAR) Location (Bus No – Bus No) UPFC Settings	17.599 22.244 - -	17.5223 22.4053 2 - 6 r = 0.0658, γ=125.58°	17.5046 22.6098 2-4 & 2-6 r = 0.038, γ=309.18°
Twice normal loading	ΣPloss(MW) ΣQloss(MVAR) Location (Bus No – Bus No) UPFC Settings	95.891 333.77 - -	95.689 333.98 6 -7 r = 0.061, γ=87.02°	95.501 335.45 2-6 & 6-7 r = 0.052, γ=305.21°
Active load increasing thrice at bus #7	ΣPloss(MW) ΣQloss(MVAR) Location (Bus No – Bus No) UPFC Settings	25.5924 50.956 - -	25.4839 51.2496 2 - 6 r = 0.065, γ=138.78°	25.4680 51.2363 2-6 & 6-7 r = 0.053, γ=335.73°

Active & Reactive load increasing thrice at bus #21	ΣPloss(MW) ΣQloss(MVAR) Location (Bus No – Bus No) UPFC Settings	24.0965 52.5682 - -	23.9970 52.8299 2 - 6 r = 0.0608, γ=194.61°	23.9858 53.1688 2 -4 & 2- 6 r = 0.0342, γ=18.43°

Table 5: Results of IEEE 30 –Bus System (Genetic Algorithm)

Cases		Status 1 (Without UPFC)	Status 2 (With one UPFC)	Status 3 (With Two UPFC's)
Normal loading	ΣPloss(MW) ΣQloss(MVAR) Location (Bus No – Bus No) UPFC Settings	17.599 22.244 - -	17.5239 22.41 2 - 6 r = 0.0658, γ=125.58°	17.5056 22.6137 2-4 & 2-6 r = 0.0374, γ=309.22°
Twice normal loading	ΣPloss(MW) ΣQloss(MVAR) Location (Bus No – Bus No) UPFC Settings	95.891 333.77 - -	95.693 333.99 6 -7 r = 0.0608, γ=84.33°	95.506 335.47 2-6 & 6-7 r = 0.0522, γ=304.92°
Active load increasing thrice at bus #7	ΣPloss(MW) ΣQloss(MVAR) Location (Bus No – Bus No) UPFC Settings	25.5924 50.956 - -	25.4970 50.7654 2 - 6 r = 0.0533, γ=168.72°	25.4715 51.2570 2-6 & 6-7 r = 0.0466, γ=44.34°
Active & Reactive load increasing thrice at bus #21	ΣPloss(MW) ΣQloss(MVAR) Location (Bus No – Bus No) UPFC Settings	24.0965 52.5682 - -	24.0053 52.8601 2 - 6 r = 0.0641, γ=200.06°	23.9862 53.1705 2 -4 & 2- 6 r = 0.0351, γ=19.20°

Table 6: Comparison between Differential Evolution Algorithm & Genetic Algorithm (IEEE 30bus)

Case	Decrease in real power loss Δ PL (KW) one UPFC		Decrease in real power loss Δ PL (KW) Two UPFC's		CPU Time (sec) Two UPFC's	
	DE	**GA**	**DE**	**GA**	**DE**	**GA**
Normal loading	76.7	76.7	94.4	93.4	10.9	100.4
Twice normal loading	202	202	390	385	13.7	193.6
Active load increasing thrice at bus #7	108.5	108.5	124.4	120.9	12.7	126.2
Active & Reactive load increasing thrice at bus #21	99.5	99.5	110.7	110.3	14.2	119.8

6. CONCLUSION

Optimal installation of FACTS device is required in achieving minimal total real power loss under different loading conditions. This paper attempted to find out the optimal location and parameters for one or two UPFC device(s) to minimize total real power loss using DE and GA techniques.

From the results it is found that in DE based optimal power flow method, the reduction of real power loss remains the same or better when compared with GA. When comparing CPU time execution, the convergence speed of DE is faster than GA and this is due to the fact that DE uses a non uniform crossover and employs a greedy selection process.

Therefore, the DE algorithm seems to be a promising approach for engineering optimization problems. With the above proposed algorithms, it is possible to locate the UPFC's in the transmission line such that proper power planning and operation can be achieved with minimum system losses.

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