International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 3 Issue 2, February - 2014

Feasible Parameter Selection to Solution of Optimal Power Flow by DE Technique

P. Ram Kishore Kumar Reddy
Associate Professor, Department of EEE, MGIT, Hyderabad

***Abstract* - With rapidly increasing demand of electrical energy and without any major appreciable reinforcement's projects to enhance power transmission networks, more brittle situation exists in operation of power system. Modern power system operating tools with Optimization techniques have been adapted to insure proper operation and security of operation to meet increasing demand and reduce generation cost to optimize resources and to satisfy customers and suppliers.**

This paper presents an algorithm for solving Optimal Power Flow problem through the application of modern heuristic method known as Differential Evolution (DE) for obtaining global minima of objective function. The objective is to minimize the total fuel cost of thermal generating units having quadratic cost characteristics subjected to limits on generator real and reactive power outputs, bus voltages, transformer taps and power flow of transmission lines.

The DE method has to be tested on 26-bus system, within this various parameters in the optimization process and their effects on convergence are to be studied and finally the feasible parameter values that effect to fit as the solution to Optimal Power Flow Problem is presented.

Keywords—Optimal Power Flow, Heuristic Method, Differential Evolution etc.,

I. INTRODUCTION

Nowadays, the electricity market is going toward open market and deregulation creating an environment for forces of competition and bargaining. Electricity utilities are in need to serve more loads through their networks and also maintain the system security. New power systems simulation tools with optimization techniques have been adapted to power systems to insure proper operation/security of the power system, meet the requirement of electricity demand, reduce cost, optimize the resources and also help to satisfy customers and suppliers.

Traditionally, in system studies, normal load flow was used to simulate performance of system under certain operational conditions. In the early stages, fuel cost optimization described as the economical dispatch was a very basic objective. Later, the load flow problem was combined with the economical dispatch problem as an optimization problem. This has formulated the optimal power flow (OPF) which provided a tool to manipulate the system variables to reduce the fuel cost while meeting certain conditions and constraints to ensure proper system operation. At later stages, the application of OPF has gone far beyond the economical dispatch problem, depending on the selection of the objective function

II. THE OPTIMAL POWER FLOW

For the planner and operator fixed generation corresponds to a snapshot only. Planning and operating requirements very often ask for an adjustment of the generated powers according to certain criteria. One of the obvious ones is the minimum of the generating cost. The application of such a criterion immediately assumes variable input powers and bus voltages which have to be determined in such a way that a minimum of the cost of generating these powers is achieved.

At this point it is not only the voltages at buses where the loads are supplied but also the input powers together with the corresponding voltages at the generator buses which have to be determined. The degree of freedom for the choice of inputs seems to be exceedingly large, but due to the presence of an objective, namely to reach the minimum of the generating cost the problem is well defined. Of course the mathematics become more demanding as compared to the original power flow problem, however, the aim still being the same, i.e. the determination of the nodal voltages in the system. They play the role of state variables from which all other quantities can be derived. It turns out that the extended problem requires a more detailed definition and different methods of solution.

The problem can be generalized by attaching different objectives to the original power flow problem. As long as the power flow model stays the same it is considered the optimal power flow problem where the objective is a scalar function of the state variables. In essence, any optimal power flow problem can be reduced to such a form.

III. DIFFERENTIAL EVOLUTION ALGORITHM

One extremely powerful algorithm from Evolutionary Computation due to convergence characteristics and few control parameters is differential evolution. Differential Evolution is an optimization algorithm that solves real-valued problems based on the principles of natural evolution using a population P of N_p floating point encoded individuals that evolve over G generations to reach an optimal solution. Each individual, or candidate solution, is a vector that contains as many parameters as the problem decision variables D. In Differential Evolution, the population size (N_p) remains constant throughout the optimization process.

$$\mathbf{P^{(G)} = [X_1^{(G)}, ---- X_{Np}^{(G)}]} \qquad \mathbf{---(1)}$$

$$\mathbf{X_i^{(G)} = [X_{1,i}^{(G)}, ---- X_{D,i}^{(G)}]^T} \qquad \mathbf{---(2)}$$
$$\mathbf{i = 1, ---- N_P}$$

Differential Evolution creates new offspring by generating a noisy replica of each individual of the population. The individual that performs better from the parent vector (target vector) and the replica (trial vector) advances to the next generation. This optimization process is carried out with three basic operations: Mutation, Crossover and Selection. First, the mutation operation creates mutant vectors by perturbing each target vector with the weighted difference of two other individuals selected randomly. Then, the crossover operation generates trial vectors by mixing the parameters of the mutant vectors with the target vectors, according to a selected probability distribution. Finally, the selection operator forms the next generation population by selected between the trial vector and the corresponding target vector those that fit better the objective function.

4. DE OPTIMIZATION PROCESS

The first step in the DE optimization process is to create an initial population of candidate solutions by assigning random values to each decision parameter of each individual of the population. Such values must lie inside the feasible bounds of the decision variable, and can be generated by equation,

$$\mathbf{X_{j,i}^{(0)} = X_j^{min} + \eta_j\,(X_j^{max} - X_j^{min}),} \qquad \mathbf{---(3)}$$
$$\mathbf{i = 1, ---- N_P\,;\; j = 1, ---- D}$$

Where $\mathbf{X_j^{min}}$ and $\mathbf{X_j^{max}}$ are respectively, the lower and upper bound of the j^{th} decision parameter and $\boldsymbol{\eta_j}$ is the uniformly distributed random number within [0, 1] generated a new for each value of j.

After the population is initialized, this evolves through the operators of mutation, crossover and selection. The mutation operator is in charge of introducing new parameters in to the population. To achieve this, the mutation operator creates mutant vectors by perturbing a randomly selected vector ($\mathbf{X_a}$) with the difference of two other randomly selected vectors ($\mathbf{X_b}$ and $\mathbf{X_c}$)) according to. All of these vectors must be different from each other, requiring the population to be of at least four individuals to satisfy this condition. To control the perturbation and improve convergence, the difference vector is scaled by a user defined constant in the range [0, 1.2]. This constant is commonly known as the scaling constant (F). This is illustrated in Fig 4.1.

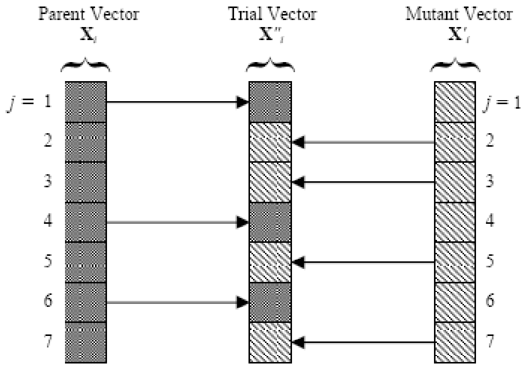

Fig.1 Method of creating Mutant Vector

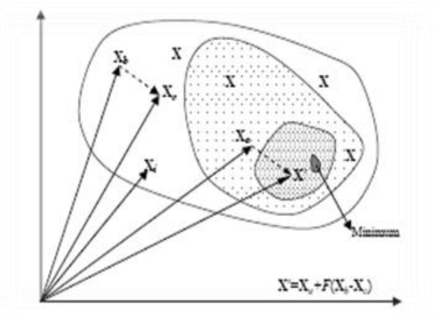

Fig.2 Method of Crossover operation

$$\mathbf{X_i^{'(G)} = X_a^{(G)} + F\,(X_b^{(G)} - X_c^{(G)})} \qquad \mathbf{---(4)}$$
$$\mathbf{i = 1, ---- N_P\,;}$$

Where $\mathbf{X_a}$, $\mathbf{X_b}$, $\mathbf{X_c}$ are randomly chosen vectors €{1, ---- Np} and a ≠b≠c≠ i. $\mathbf{X_a}$, $\mathbf{X_b}$, and $\mathbf{X_c}$ are generated anew for each parent vector. F is the scaling constant.

The crossover operator creates the trial vectors which are used in the selection process. A trial vector is a combination of a mutant vector and a parent (target) vector performed based on probability distributions. For each parameter, a random value based on binomial distribution (preferred approach) is generated in the range [0, 1] and compared against a user defined constant referred to as the crossover constant. 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.

The Figure.2 shows how the crossover operation is performed.

The cross operation maintains diversity in the population, preventing local minima convergence. The crossover constant (C_R) must be in the range of [0, 1]. A crossover constant of one means the trial vector will be composed entirely of mutant vector parameters. A crossover constant near zero results in more probability of having parameters from the target vector in the trial vector. A randomly chosen parameter from the mutant vector is always selected to ensure that the trial vector gets at least one parameter from the mutant vector even if the crossover constant is set to zero.

$$\mathbf{X_{j,i}''^{(G)} = X_{j,i}'^{(G)} \text{ if } \eta_j' \leq C_R \text{ or } j=q \quad --- (5)}$$
$$\mathbf{X_{j,i}^{(G)} \text{ otherwise}}$$
$$\mathbf{i = 1, ---- N_P ;\ j = 1, ---- D}$$

Where q is a randomly chosen index €{1, - - - - D} that guarantees that the trial vector gets at least one parameter from the mutant vector; η_j' is a uniformly distributed random number with [0, 1) generated anew for each value of j. $X_{j,i}^{(G)}$is the parent (target) vector, $X_{j,i}'^{(G)}$the mutant vector and $X_{j,i}''^{(G)}$the trial vector.

The selection operator chooses the vectors that are going to compose the population in the next generation. This operator compares the fitness of the trial vector and the fitness of the corresponding target vector, and selects the one that performs better. The selection process is repeated for each pair of target/trial vector until the population for the next generation is complete.

$$\mathbf{X_i^{(G+1)} = X_{j,i}''^{(G)}} \text{ if } f(\mathbf{X_{j,i}''^{(G)}}) \leq f(\mathbf{X_{j,i}^{(G)}}) \quad \mathbf{--- (6)}$$
$$\mathbf{X_i^{(G)} \text{ otherwise}}$$
$$\mathbf{i = 1, ---- N_P ;}$$

V. DE BASED OPF ALGORITHM

Differential Evolution has been applied to problems from several areas. Some power engineering problems have been solved with DE including: Distribution systems capacitors placement, harmonics voltage distribution reduction and passive shunt harmonic filter planning. DE has also been used in the design of filters, neural network learning, fuzzy logic application, and optimal control problems, among others.

The objective function of OPF

Minimize $$F_{COST} = \sum_{i=N_{pq}+1}^{N} F_{COST(i)}(P_{Gi})$$

Minimize $$F_{COST} = \sum_{i=N_{pq}+1}^{N} F_{COST(i)}(P_{Gi}) =$$

$$\mathbf{a_i P_{Gi}^2 + b_i P_{Gi} + c_i} \quad \mathbf{--- (7)}$$

Where $N_g = N - N_{pq}$ = No. of generating units to be optimized
N_{pq} = No. of fixed load PQ buses

Subject to constraints,

$$\left.\begin{matrix} \mathbf{g(x) = 0} \\ \mathbf{h(x) \leq 0} \end{matrix}\right\} \quad \mathbf{--- (8)}$$

g(x) =0 is the equality constraints and represent typical load flow equations.

h(x) ≤0 *is* the system operating constraint

A. Dependent Variables

X is the vector of dependent variables consisting of slack bus power P_{G1}, load bus voltages V_L , generator reactive power outputs Q_G , and transmission line loadings S_l . Hence, X can be expressed as

$X^T=[P_{G1}, V_L, Q_G, S_l]$

i.e., $X^T= [P_{G1}, V_{L1}, ---- V_{LNpq}, Q_{G1}, ---- Q_{GNg}, S_{l1}, ---- S_{lNl}]$

Where N_{pq} ,N_g ,N_l are number of load buses, number of generators and number of transmission lines respectively

B. Independent Variables

U is the vector of independent variables consisting of generator voltages V_L , generator real power outputs P_G , except at the slack bus P_{G1}, and transformer tap settings T. Hence, U can be expressed as

$U^T= [V_G, P_G, T]$

i.e., $U^T = [V_{G1}, ---- V_{GNg}, P_{G1}, ---- P_{GNg}, T_1, ---- T_{Nt}]$

Where N_t is the number of the regulating transformers

C. *Initialization*

The first step in this algorithm is to create an initial population. All the independent variables [V_G, P_G, T] have to be generated according to formula (3), where each independent parameter of each individual in the population is assigned a value inside the given feasible region of the generator. This creates parent vectors of independent variables for the first generation. As they have created within their limits, they readily satisfy the corresponding inequality constraints. To find dependent variables $X^T= [P_{G1}, V_L, Q_G, S_l]$ corresponding to each individual, Newton- Raphson power flow solution is implemented. After getting all vectors corresponding to dependent variables, constraint-handling method of penalty functions is applied to handle the inequality constraints related to dependent variables. Penalty factors corresponding to each dependent variable of each individual in population have to be calculated. If they violate a limit whether lower or upper, difference of that value and corresponding limit violated was taken as penalty index and it is multiplied with a constant so as to match with basic objective function i.e., fuel cost. The penalty functions for slack bus power, voltages of load buses, line flows and reactive power generations are considered to calculate fitness of each population member. Fitness includes fuel cost function and also penalties corresponding to dependent variables. Inclusion of these penalties in fitness gives us a great opportunity to assign better fitness to that particular population member whose control parameters are within the operational limits in addition to minimum fuel cost.

VI. ALGORITHM FOR OPF FROM DE CANDIDATE SOLUTION

This is the algorithm for Optimal Power Flow for the considered system of study. This has been developed as a separate subroutine within which there is an other subroutine for ordinary Power Flow. This Optimal Power Flow subroutine is evaluated for each of the obtained DE candidate solution in the population concerned at the particular iteration and evaluated in each iteration for all candidate vectors in the population of current iteration. The number of times this subroutine is evaluated depends on the population size and the iteration maximum value.

In brief this subroutine for the obtained candidate solution from the Differential Evolution subroutine, which is the generation of all the generator buses in the system (except the slack bus) it checks with the limits of the corresponding generator bus, whether there is any violation of such limits (or) not. Next the ordinary Power Flow is run for the above data to obtain the contribution of slack bus also, which is a generator bus. Finally with the cost function existing for each generator, the total cost for generation of active power in the system is found.

Along with the generator contribution the power flow results with the voltage profile of each bus in the system and the total loss for the given contribution of generator.

Here the optimum solution is reached where the Total cost of generation and the Line Losses are at minimum. The algorithm for the above implementation is as explained below.

Step 1: Get the current Population matrix with the individual candidate solution vectors.

Step 2: For the obtained candidate solution vector of current iteration, at first generation is checked with the limits of generators Real Power output specified for each generator (except slack bus), as given in the Cost function matrix. If it crosses the extreme it is fixed to that extreme itself, if not hold the obtained value.

Step 3: This obtained generations are substituted at the corresponding buses in the busdata matrix of the system considered.

Step 4: Now for obtained generations an ordinary load flow is run to obtain new generations at all buses including slack bus.

Step 5: This is adjusted with the set base MVA of the system.

Step 6: Now with generations, the cost of generating such power from existing generator is found by their individual cost functions. At last new cost of generation is obtained.

Step 7: From the same load flow, the voltage at different buses in system is obtained, which is checked for any violation due to optimization process.

Step 8: The individual generator contribution is obtained at last of the subroutine

Step 9: Stop the function evaluation.

In this subroutine an ordinary load flow is made to evaluate by Newton-Raphson method. This is the most widely used method for solving simultaneous nonlinear algebraic equations is the Newton-Raphson method. Newton's method is a successive approximation procedure based on an initial estimate of the unknown and the use of Taylor's series expansion.

After the iterative solution of bus voltages, the next step is the computation of the line flows and line losses. This is formulated by the basic equations for the bus considered from current equations. Even all the load flow programs result with this calculation.

VII. SIMULATION AND RESULTS

Different cases of simulation was performed by repeatedly executing the Optimal Power Flow program for different values of DE variables, and the total cost of generation is found with the losses calculated for that particular combination. Some of which are as shown below

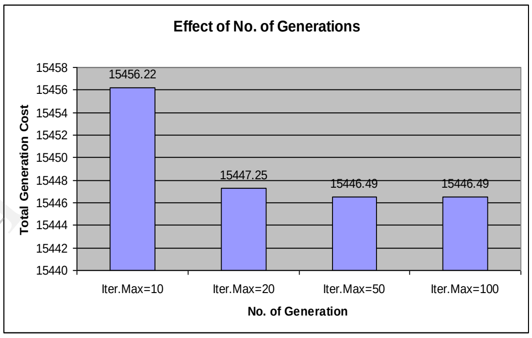

Fig 3 Effect of Number of Generations

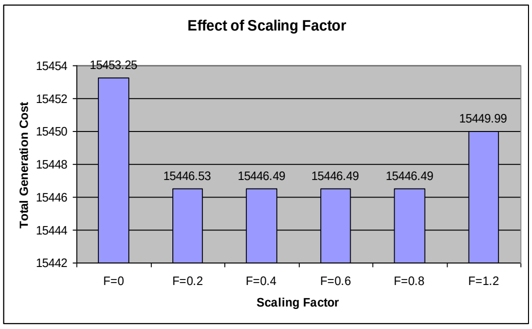

Fig 4 Effect of Scaling Factor

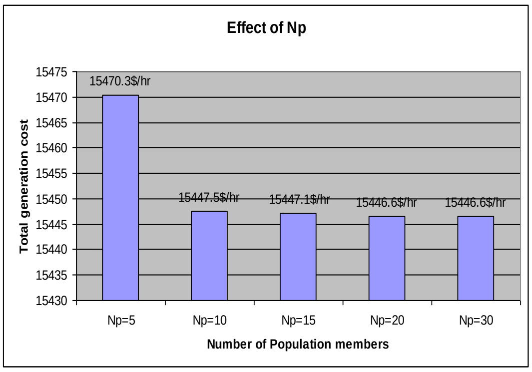

Fig. 5 Effect of Number of Population members

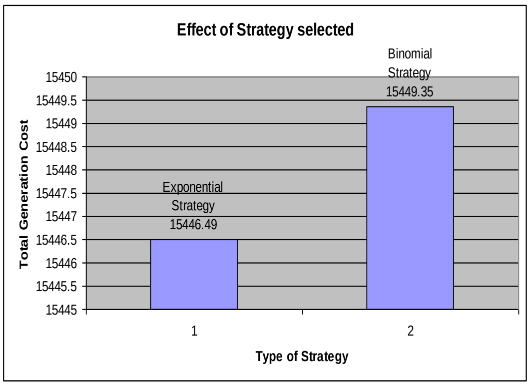

Fig. 6 Effect of Strategy selected

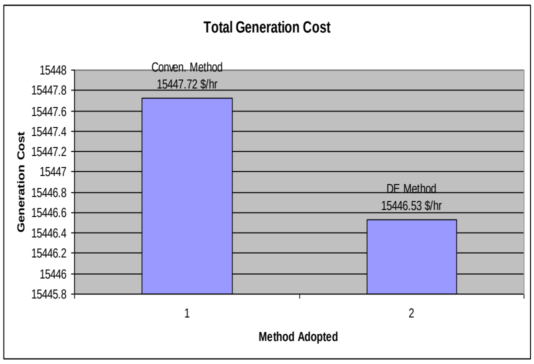

Fig.7 Cost Comparison for 26-bus system

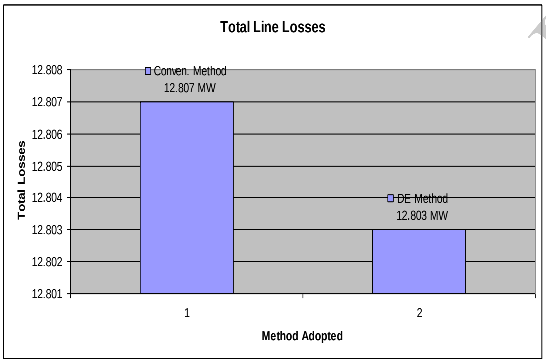

Fig. 8 Losses Comparison for 26-bus system

The following are the conclusions obtained from the above simulations:

i. For a system with high number of bus, the solution is getting converged for only with considerable number of iterations (i.e., generations). This mean it needs to have at least minimum number of generation to attain the global minima. The effect is depicted in Table 3.

ii. With C_R constant for a particular case, for increasing F as mentioned in Table (1) and (2), the solution is changing for different values of F. At first due to F=0, cost it maximum. As the F increases cost at first decreases reaches to an optimum value and thereafter with increase in F cost also increases. From this we conclude that value of F has considerable effect towards attainment of global minima. Hence it value should be within [0.4, 0.8]. This is depicted as in Figure 4.

iii. With C_R constant for a particular case, for increasing F as mentioned in Table (1) and (2), the total cost is getting same for more combinations. It means the solution is getting converged for same value for higher F and $C_{R,}$ except at F=0, as depicted in Figure 3.

iv. The Number of population members selected has also effect towards the convergence of optimal solution. This is clearly exhibited in systems with more number of buses, especially in 26-bus system the effect is clearly tabulated in Table 4 and plotted in Figure 5.

v. For a system with high number of buses, the type of strategy adopted has its effect. The effect is depicted in Figure 6. This states that Exponential strategy gives dominant effect than Binomial strategy.

vi. Below is the comparison of DE with the Conventional method, an appreciable amount of savings in cost is obtained. But the losses are not confronting appreciably. However, this is the case only for systems with low number of bus, but in practical case with more number of buses, this effect more.

On comparing the DE method with the conventional method of obtaining solution of Optimal power flow the following conclusion was obtained.

Table 1 Results of 26-bus system for C_R = 0.4 and varying F

C_R = 0.4	$/hr	Losses (MW)
F=0	15453.25	12.871
F=0.2	15446.53	12.803
F=0.4	15446.49	12.809
F=0.6	15446.49	12.809
F=0.8	15446.49	12.811
F=1.2	15449.99	12.624

Table 2 Results of 26-bus system for members C_R = 0.8 and varying F

C_R = 0.8	$/hr	Losses (MW)
F=0	15493.61	13.283
F=0.2	15447.39	12.768
F=0.4	15446.49	12.809
F=0.6	15446.49	12.809
F=0.8	15446.49	12.809
F=1.2	15446.86	13.303

For $N_p = 20$	
Iter.Max.	**Total Cost ($/hr)**
10	15456.22
20	15447.25
50	15446.49
100	15446.49

Table 4 Effect of Number of Population

For Total Number of iteration = 100	
N_p	**Total Cost ($/hr)**
5	15470.3
10	15447.5
15	15447.1
20	15446.6
30	15446.6

Table 5 Cost Comparison for 26-bus

No. of bus	Parameter considered	Solution by Conventional Method	Solution by solving OPF by DE
26-bus system	Total Generating Cost	15447.72 $/hr	15446.53$/hr
	Total Losses	12.807 MW	12.803 MW

VIII. CONCLUSION

The Differential Evolution method being an heuristic method of solving optimization problem, do not give any assurance towards convergence of solution with specified number of iterations (or) number of population members. So, in this aspect a clear analysis of this method to a power system optimization problem, termed as the Optimal Power Flow (OPF) is clearly presented. Their effects were clearly analyzed and presented as a plot.

Hence, the above analysis concludes that even though being a heuristic method the solution is getting converged only after a considerable number of iterations only. The savings in cost is very narrow for the considered 26 bus system, but in practice a power system comprising several thousands of bus the savings in generating cost may be appreciable.

APPENDIX

Data of 26 bus System

The sample 26-bus system has 6 generators and loads connected to 23 buses, 4 tap changing transformers, 9 shunt capacitors.

Shunt Capacitor Data	
Bus No	Mvar
1	4.0
4	2.0
5	5.0
6	2.0
9	3.0
11	1.5
12	2.0
15	0.5
19	5.0

Regulated Bus Data			
Bus No.	Voltage Magnitude	Min. Mvar Capacity	Max. Mvar Capacity
2	1.020	40	250
3	1.025	40	150
4	1.050	40	80
5	1.045	40	160
26	1.015	15	50

Generator Real Power Limits		
Gen.	**Min. MW**	**Max. MW**
1	100	500
2	50	200
3	80	300
4	50	150
5	50	200
26	50	120

Transformer Designation	**Tap Setting Per Unit**
2 - 3	0.960
2 - 13	0.960
3 - 13	1.017
4 – 8	1.050
4 – 12	1.050
6 – 19	0.950
7 – 9	0.950

The generator's operating cost is $/h, with $P_i$in MW are as follows:

$$C_1 = 240 + 7.0P_1 + 0.0070P_1^2$$
$$C_2 = 200 + 10.0P_2 + 0.0095P_2^2$$
$$C_3 = 220 + 8.5P_3 + 0.0090P_3^2$$
$$C_4 = 200 + 11.0P_4 + 0.0090P_4^2$$
$$C_5 = 220 + 10.5P_5 + 0.0080P_5^2$$
$$C_{26} = 190 + 12.0P_{26} + 0.0075P_{26}^2$$

REFERENCES

1. R.Gnanadas, P.Venkatesh, Narayana Prasad Padhy, “Evolutionary Programming Based Optimal Power Flow for Units with Non-Smooth Fuel Cost Functions”, Electric Power Components and Systems, Vol.33, 2005, pp. 1245-1250.
2. Jason Yuryevich, Kit Po Wong, “Evolutionary Programming Based Optimal Power Flow Algorithm”, IEEE Transactions on Power Systems, Vol. 14, No. 4, November 1999, pp.1245-1250.
3. C.E.Lin, G.L. Viviani, “Hierarchial Economic Dispatch For Piecewise Quadratic Cost Functions,” IEEE Trans. Power apparatus and systems, Vol. PAS-103, No. 6, pp. 1170-1175, June 1984.
4. Differential Evolution Home page http//www.icsi.berkely.edu/storn/code.html.
5. Differential Evolution based Optimal dispatch algorithms, an Master of Science, thesis by Peroz Guerrero, University of PUERTO RICO.