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OPTIMAL POWER FLOW SOLUTION USING EVOLUTIONARY PROGRAMMING

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Abstract- This paper develops an efficient and reliable evolutionary programming algorithm for solving the optimal power flow (OPF) problem. The class of curves used to describe generator performance does not limit the algorithm and the algorithm is also less sensitive to starting points. In the paper, the main elements of the evolutionary programming based OPF algorithm is presented. The algorithm is then demonstrated on the IEEE 30 bus test system.

Keywords- Optimal Power Flow, Evolutionary Programming, Optimization.

I. INTRODUCTION

Solving the power flow problem is fundamental to the unbundling of transmission costs associated with transmission open access and is of increasing in power system operation under de-regulated environment of electricity industry. The computational difficulties in solving the OPF problem have limited its use in power system operations.

OPF is a non-linear programming problem, and is used to determine optimal outputs of generators, bus voltage and transformer tap setting in power system with an objective to minimize total production cost while the system is operating within its security limits since OPF was introduced, several methods have been employed to solve this problem, Linear programming method, gradient method and Quadratic programming. However all of these methods suffer from three main problems. Firstly, they may not be able to provide optimal solution and usually getting stuck at a local optimal.

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Secondly, all these methods are based on assumption of continuity and differentiability of objective function, which is not actually existed in a practical system.

Finally, all these methods cannot be applied with discrete variables, which are transformer taps. It is therefore important to develop new, more general and reliable algorithms, which are capable of incorporating new constraints arising from open access, non-convex solution surfaces. One such technique is that of Evolutionary Programming. The EP technique is a stochastic optimization method in the area of evolutionary computation, which uses the mechanics of evolution to produce optimal solutions to a given problem. It works by evolving a population of candidate solutions towards the global minimum through the use of a mutation operator and selection scheme. The EP technique is particularly well suited to non-monotonic solution surfaces where many local minima may exist.

This paper develops an EP based OPF solution algorithm [EP-OPF] which makes use of an EP load flow. The method is capable of determining the global optimum solution to the OPF for a range of constraints and objective functions. The algorithm is not sensitive to starting points and is capable of handling non-convex generator cost curves. The performances of the algorithm when applied to the IEEE 30-bus test system under different generator input-output curves are presented.

A . Nomenclature

N_b = number of buses
N_g = number of generators
t_k = transformer tap setting at branch k
P_{sl} = active power generation at slack bus
V_i = bus voltage at bus i
P_i , Qi = active and reactive power injection at bus i
P_{gi}^{max} , P_{gi}^{min} = upper and lower limit of active power generation at bus i
Q_i^{max} ,Q_i^{min} = upper and lower limit of reactive power generation at bus i
V_{Li}^{max} ,V_{Li}^{min} = lower and upper voltage limit of ith load bus
V_{Gi}^{max} ,V_{Gi}^{min} = lower and upper voltage limit of generator bus i
t_i^{max} ,t_i^{min} = lower and upper limit of transformer tap setting at branch k

S_l^{max}	= maximum MVA rating of transmission line
F_T	= total fuel cost
a_j, b_j, c_j	= cost coefficients of the j-th generator

II. OPTIMAL POWER FLOW

The optimal power flow problem seeks to optimize steady state power system performance with respect to an objective f while subject to numerous constraints. For optimal active and reactive power dispatch, the objective function, f, is that of total generation cost. Other objectives may include minimization of transmission losses and voltage level optimization. Mathematically this may be stated as:

$$\min f(x,u)$$

Subject to:

$$g(x,u) = 0$$
$$h(x,u) \le 0$$

Where u is the vector of control variables (these include generator active power/voltage levels and transformer tap settings); x is the vector of dependent variables (load (PQ) node voltages, generator reactive powers); $f(x,u)$ is the objective to be optimized; g(x,u) are the nodal power constraints; and h(x,u) are the inequality constraints on dependent and independent variables.

In the OPF problem under consideration, we are interested in a solution that minimizes the total operating cost of the generating units while satisfying the several unit and system constraints.

This is mathematically stated as,

III. MATHEMATICAL REPRESENTATION

B. Objective Function

$$\text{Minimize } F_T = \sum_{i=1}^{N_g} (a_i + b_i P_{gi} + c_i P_{gi}^2) \quad \$/hr$$

Subject to

1) Load flow constraints

$$P_i = V_i \sum_{j=1}^{N_b} V_i \left[G_{ij} \cos\theta_{ij} + B_{ij} \sin\theta_{ij}\right]$$

$$Q_i = V_i \sum_{j=1}^{N_b} V_i \left[G_{ij} \cos\theta_{ij} - B_{ij} \sin\theta_{ij}\right]$$

2) Voltage constraints

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

3) Unit constraints

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

$$Q_i^{min} \le Q_{gi} \le Q_i^{max}$$

4) Transformer tap setting constraint

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

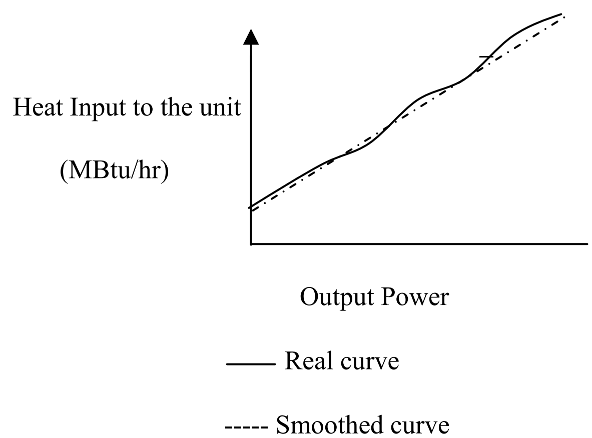
5) Transmission line flow constraints

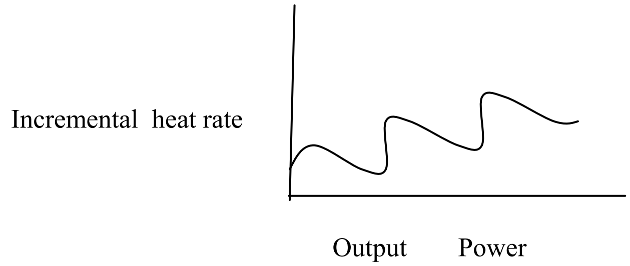
$$S_i \le S_l^{max}$$

IV. VALVE POINT EFFECT

Large steam turbine generators usually have a number of steam admission valves that are opened in sequence to obtain ever-increasing output from the unit. As the unit loading increases, the input to the unit increases. However, when a valve is just opened, the throttling losses increase rapidly so that the input heat increases rapidly and the incremental heat rate rises suddenly. This gives rise to the non-smooth type of heat input and discontinuous type of incremental heat rate characteristics. This type of characteristic should be used in order to schedule steam units accurately, but it cannot be used in traditional optimization methods because it does not meet the convex condition.

V. NON CONVEX CURVES





VI. EVOLUTIONARY PROGRAMMING [EP]

EP seeks the optimal solution by evolving a population of candidate solutions over a number of generations or iterations. During each iteration, a second new population is formed from an existing population through the use of a mutation operator. This operator produces a new solution by perturbing each component of an existing solution by a random amount. The degree of optimality of each of the candidate solutions or individuals is measured by their fitness, which can be defined as a function of the objective function of the problem. EP is a computational intelligence method in which an optimization algorithm is the main engine for the process of three steps; namely, natural selection, mutation and competition. According to the problem each step could be modified and configured in order to achieve the optimum results. It is a stochastic optimization strategy, which places emphasis on the behavioral linkage between parents and their offspring. However, mutation ensures the functionality of the next generation. Therefore EP tends to generate more effective and efficient searches.

VII. FEATURES OF EP

EP belongs to the class of population based search strategies. They operate on populations of real values that represent parameter set of the problem to be solved over some finite ranges. Each representation is an individual in the EP population. The population is initialized with random individual at the start of EP run. The EP searches the space of possible real values for better individuals. The search is guided by fitness values returned by the environment. This gives a measure of how adapted each individual is in terms of solving the problem and hence determines its probability of appearing in future generations. EP uses two types of rules in its search for highly fit individuals, namely the selection rule and combination rule. The selection rule is used to determine the individuals that will be represented in the next generation. It includes competition in which each individuals in the combined population has to compete with some other individuals to get chance to be transcribed to the next generation. The combination rule operates on selected individuals to produce new individuals that appear in the next generation. The selection mechanism is based on a fitness measure or objective function values, defined on each individual in the population. The combination rule is used to introduce new individuals into current population. EP uses only one operator in the combination process. The most commonly used evolutionary operator is mutation. Mutation is the random occasional alteration of the information contained in the individual. The combination rule acts on individuals that have been previously selected by the selection mechanism.

1) Initialization- The initial population of control variables is selected randomly from a set of uniformly distributed control variables ranging over their upper and lower limits. Here the control variable are P_j=[P_g^t V_g^u,T^v],where t=1 to number of generator (except slack bus),u=1 to number of AVR, v= 1 to number of tap changing transformer, i =1,2…m where m is the population size from the sets of uniform distributions ranging from [P_g^{min}, P_g^{max}], [V_g^{min}, V_g^{max}], [T^{min},T^{max}].

2) Statistics- The maximum fitness f_{max} minimum fitness f_{min}, the sum of fitness, and average fitness f_{avg} of this generation are calculated.

$$f_{max} = \{ f_i \mid f_i \geq f_j \ \ \forall f_j, j = 1.....m \}$$

$$f_{min} = \{ f_i \mid f_i \leq f_j \ \ \forall f_j, j = 1.....m \}$$

$$f_\Sigma = \sum_{i=1}^{m} f_i$$

$$f_{avg} = f_\Sigma / m$$

3) Mutation-Each selected parent, for example Pi, mutated and added to its population following the rules:

$$P_{i+m,j} = P_{i,j} + N\left(0, \beta(x_{jmax} - x_{jmin}) f_i/f_{max} \right), j=1,2,......,n$$

Where n is the number of decision variables in an individual, $P_{i,j}$ denote the j^{th} element of the i individual .$N(\mu,\sigma^2)$ represents a Gaussian random variable with mean μ and variance σ^2; f_{max} is the maximum fitness value of the generation which is obtained in statistics; x_{jmax} and x_{jmin} are the maximum and minimum limits of the j^{th} element; and β is the mutation scale, $0 \leq \beta \leq 1$,that adaptively decreased during generations. If any mutated value exceeds its limit, it will be given the limit value.

$$\beta(k+1) = \begin{cases} \beta(k) - \beta_{step} & \text{if } f_{min}(k) \text{ unchange} \\ \beta(k) & \text{if } f_{min}(k) \text{ decrease} \\ \beta_{final} & \text{if } \beta(k) - \beta_{step} < \beta_{final} \end{cases}$$

$$\beta(0) = \beta_{init}$$

The initial β is 1 then it decreases by β_{step}, which is set from 0.001 to 0.01. β_{final} is set to 0.005. β values depend on the number of generations and the complexity of the system. The mutation process allows an individual with larger fitness to produce more offspring for the next generation.

4) Inner Loop Convergence Criterion-The convergence is achieved when either the maximum fitness value converges to the minimum fitness value or the generations reach the maximum generation number. If this condition is met, the process will go to the next step; otherwise, the processes will go back to the Inner Loop Start.

6) Outer Loop Convergence Criterion-The convergence is achieved when either all the state variables, voltage magnitudes of load buses and reactive power generations, transmission line flows are within limits or the outer loops reach the maximum number. If the condition is met, the program will stop. If one or more state variables violate their limits, the penalty factor of these variables will increase, and the process will go back to the Outer Loop Start.

VIII. OBJECTIVE FUNCTION FOR EP-OPF:

$$[Min]F_T = F_T + \sum_{j=1}^{NVB} V_j + \sum_{i=1}^{NG} Q_j + \sum_{i=1}^{NL} S_l$$

Where NVB is the number of voltage violating buses, NG is number of generator for which reactive power generation is not within the limits and NL is the number of transmission lines for which the line flows exceeds the maximum limits.

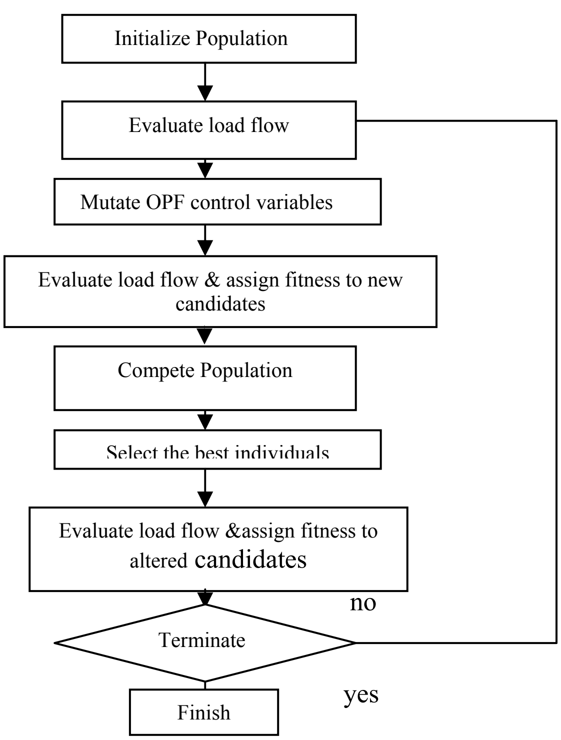
$$V_j = \begin{cases} \lambda_1(V_{Li} - V_{Li}^{max})^2 & \text{if } V_{Li} > V_j^{max} \\ \lambda_1(V_{Li} - V_{Li}^{min})^2 & \text{if } V_{Li} > V_j^{min} \end{cases}$$

$$Q_j = \begin{cases} \lambda_2(Q_j - Q_j^{max})^2 & \text{if } Q_j > Q_j^{max} \\ \lambda_2(Q_j - Q_j^{min})^2 & \text{if } Q_j > Q_j^{min} \end{cases}$$

$$S_l = \lambda_3(S_l - S_l^{max})^2 \text{ if } S_l \le S_l^{max}$$

Where λ_1 is the penalty for load bus voltage violation, λ_2 is the penalty for reactive power violation of the generator and λ_3 is the penalty for transmission line flow violation.

IX. FLOWCHART FOR EP-OPF



X. SIMULATION RESULTS

The EP-based OPF algorithm was applied to the IEEE 30-bus test system. Two sets of generator cost curves were used to illustrate the robustness of the technique. The first case considered is where all curves are quadratic in cases b some of the cost curves are replaced with either piece-wise quadratics or quadratics with sine components. Therefore in cases b, there are many local optimal solutions for the dispatch problem and as a result the conventional methods cannot determine the global optimum solution. The problem is therefore well suitable for validating the developed algorithm.

The EP-based OPF algorithm was implemented using the Mat lab 6 Software and the software program was executed on a *200-MHZ* Pentium Pro computer. The specific settings for the algorithm and system date are summarized in Appendix I. In all cases, the standard *IEEE 30-BUS* loading is used.

Case(a):Quadratic Cost Curves-In this case the unit cost curves are represented by quadratic functions from [12] and are summarized in Table1 below. The program was run 100 times with the settings of Appendix I. The average cost of the solution obtained was \$803.09 with the minimum being \$802.92 and the maximum of \$803.26. The average execution time was 51.4 seconds. The solution detail for the minimum cost is compared with Genetic Algorithm and the results are provided in Table 3.

Table 1

bus no.	P_G min	P_G max	Q_G min	Q_G max	Cost Coefficient		
					a	b	c
1	50	200	-20	250	0.00	2.00	0.00375
2	20	80	-20	100	0.00	1.75	0.01750
5	15	50	-15	80	0.00	1.00	0.06250
8	10	35	-15	60	0.00	3.25	0.00834
11	10	30	-10	50	0.00	3.00	0.02500
13	12	40	-15	60	0.00	3.00	0.02500

Generation input / output function Ci = $a_i + b_i Pg_i + c_i Pg_i^2$

Case (b): Sine Components-In this case the unit cost curves of the generators connected to buses 1 and 2 were quadratics with a sine component superimposed upon them. The sine component was used to represent the valve-point loading effects [4, 11]. The data for these curves are provided in Table 2. As in case (b) above, node 1 was taken to be the slack bus for the studies. The program was run 100 times with the minimum solution cost being \$924.05 and average solution cost being \$925.20. The solution details for average cost are provided in Table 2.

Table 2.

Bus. no	min P_G	max P_G	Cost Coefficient				
			a	b	C	d	e
1.	50	200	150.0	2.00	0.0016	50.00	0.0630
2.	20	80	25.0	2.50	0.0100	40.00	0.0980

Generation input / output cost function

$$C_i = a_i + b_i Pg_i + c_i Pg_i^2 + |d \sin (e(Pg_i^{min} - Pg_i)) |$$

Table 3.Case (a)

Variable	EP-OPF		GA-OPF
	Min-Cost	Avg-Cost	
P_1	175. 6232	175. 0365	173. 721
P_2	48. 5246	48. 2553	50. 381
P_5	21. 2304	21. 8708	21. 804
P_8	23. 0875	22. 8156	23. 586
P_{11}	12. 1226	12. 2143	10. 841
P_{13}	12. 3844	12. 7514	12. 328
V_1	1. 0499	1. 0499	1. 0484
V_2	1. 0349	1. 0357	1. 0310
V_5	1. 0116	1. 0054	1. 0024
V_8	1. 0219	1. 0173	1. 0143
V_{11}	1. 1000	1. 0832	1. 0976
V_{13}	1. 0386	1. 0389	1. 0690
t_{11}	0. 9315	1. 0046	1. 0250
t_{12}	1. 0271	1. 0807	0. 9250
t_{15}	1. 0054	1. 0500	1. 0000
t_{36}	1. 0064	1. 0313	0. 9750
Total Cost \$/hr	802. 9228	803. 0912	803. 257

Table 4.Case (b)

EP-OPF		
	Avg-Cost	Min-Cost
P_1	199. 9021	199. 6642
P_2	20. 1511	20. 0119
P_5	24. 7996	25. 2596
P_8	20. 8429	19. 7833
P_{11}	12. 8449	12. 4365
P_{13}	15. 6894	16. 8855
V_1	1. 0500	1. 0500
V_2	1. 0306	1. 0292
V_5	1. 0289	1. 0096
V_8	1. 0235	1. 0290
V_{11}	0. 9847	1. 0059
V_{13}	1. 0825	1. 0649
t_{11}	1. 0565	1. 0097
t_{12}	0. 9682	0. 9735
t_{15}	1. 0358	1. 0738
t_{36}	0. 9760	0. 9505
Total cost	925. 2075 \$/hr	924. 0560 \$/hr

XI. CONCLUSION

An evolutionary-programming-based optimal power flow algorithm (EP-OPF) has been developed. It has been tested for 2 case studies in an IEEE 30- bus system. The results obtained in Evolutionary Programming are compared with Genetic Algorithm. For case(a) presented in table 4. This algorithm is efficient and reliable even in non – linear cases such as value point loading (case b). The proposed algorithm produced optimal results irrespective of the cost functions.

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APPENDIX I

System Data- The load flow data for the system is that of the standard IEEE30bus test system. Branches 11, 12, 15 and 36 are in phase tap-changing transformers with allowable tapping ranges of ±10% with a step size of 1%. The lower voltage magnitude limits is 1.05p.u for node 1 and all load nodes, all other generation nodes have an upper limit of 1.10p.u. This date may all be found in [12]. The load flow convergence tolerance is 10^{-3}p.u.

Algorithm parameter settings- the population size is set at 30 and the number of iterations is set at 50.

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