International Research Journal of Engineering and Technology (IRJET) e-ISSN: 2395-0056
Volume: 02 Issue: 04 | July-2015 www.irjet.net p-ISSN: 2395-0072

# Heuristic technique for optimal power flow in a Power system using facts controller (TCSC)

[1]G.Rahul Varma, [2]Dr.G.V.Siva Krishna Rao

*[1]Student, EEE department, AUCE (A), A.P., INDIA*
*[2]Professor, EEE department, AUCE (A), A.P., INDIA*

---

**Abstract:** The Optimal Power Flow solution with different objective functions is presented in this paper. The different objective functions include fuel cost minimization and active power loss minimization. This is achieved using Genetic Algorithm (GA), a heuristic technique proved to be efficient and widely used. The optimal settings of the power system are determined with fuel cost minimization as objective function using basic optimal power flow solution. Active power loss has been taken as objective function for reactive power optimization. The fuel cost minimization and active power loss minimization are taken as objective functions with Thyristor Controlled Series Compensator (TCSC) device by OPF solution. The total fuel cost and active power loss are minimized using TCSC and the results are compared to the values that are obtained without TCSC. The Genetic Algorithm is applied to study all the above cases. It is tested on standard IEEE 30 bus and 75 bus systems and the results are presented.

## 1. Introduction

Optimal Power Flow (OPF) is a useful tool in modern Energy Management System. The OPF optimizes the Power System operating objective function while satisfying a set of equality and inequality constraints. The equality constraints are power flow equations and inequality constraints are the limits of power system dependent variables. The control variables include generator active powers, the generator bus voltage magnitudes, the transformer tap settings and reactive power of switchable shunt devices, while the functional operating constraints include the load bus voltage magnitudes, the generator reactive powers, the line flows and slack bus power.

OPF has been applied to regulate generator active power outputs and voltages, shunt capacitors/reactors, transformer tap settings and other controllable variables to minimize the fuel cost, network active power loss, while keeping the load bus voltages, generator reactive power outputs, network power flows and all other state variable in the power system in their operational and secure limits. In its most general formulation, the OPF is a nonlinear, non convex, large-scale, static optimization problem with both continuous and discrete control variables. Even in the absence of non convex unit operating cost functions, unit prohibited operating zones, and discrete control variables, the OPF problem is non convex due to the existence of the nonlinear (AC) power flow equality constraints. The presence of discrete control variables, such as switchable shunt devices, transformer tap positions, phase shifters, FACTS controllers further complicates the problem solution.

 

## 2. PROBLEM FORMULATION

### 2.1 Problem Variables

The OPF problem is to optimize the steady state performance of the power system in terms of the objective function while satisfying several equality and inequality constraints. In general, OPF is formulated as a constrained optimization problem

Minimize $J(x,u)$

Subject to

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

$u$ : Vector of problem control variable
$x$ : Vector of system state variables
$J(x,u)$: Objective function to be minimized
$g(x,u)$: Equality Constraints represents nonlinear load flow equations.
$h(x,u)$ : Inequality Constraints i.e. system functional operating constraints.
Where $u$ is a vector of control variables consisting of generator voltages $V_G$, generator real power outputs $P_G$ except at slack bus $P_{G_1}$, transformer tap settings $T$ and shunt VAR compensation $Q_c$. Hence $u$ can be expressed as

$$u^T = [V_{G_1} \ldots V_{G_{NG}}, P_{G_2} \ldots P_{G_{NG}}, T_1 \ldots T_{NT}, Q_{C_1} \ldots Q_{C_{NC}}]$$

### 2.2 Objective Functions

***J*** is the objective function to be minimize, which is one of the following:

*(i) Fuel cost minimization*:

The objective function $J$ is considered as total Fuel Cost

$$J = \sum_{i=1}^{NG} f_i (\$/hr) \quad \ldots (2.6)$$

Where $f_i$ is the fuel cost of i th generator

$NG$ is the number of generators

Generator cost curves are represented by quadratic functions as follows

$$f_i = a_i + b_i P_{G_i} + c_i P_{G_i}^2 (\$/hr)$$

... (2.7)

Where $a_i, b_i$, $c_i$ are cost coefficients of ith generator

$P_{G_i}$ is real power generation of unit i

*(ii) Loss minimization:*

The objective function $J$ is considered as active power loss of the system

$$J = f_c(x,y) = \sum_{i=1}^{nline} Loss_i$$

... (2.8)

Where $nline$ is the number of branches
$x$ is continuous variables
y is discrete variables

*(iii)Active power loss and fuel cost minimization with TCSC*

To relieve over loaded lines TCSC are incorporated in OPF solution. Here the objective is

active power loss and fuel cost minimization with TCSC.

## 3.1 The Proposed GA Algorithm

Genetic Algorithms (GAs) were invented and developed by John Holland. He invented genetic algorithm with decision theory for discrete domains. Holland emphasized the importance of recombination in large populations.

Genetic algorithms are search algorithms based on the mechanics of natural selection and natural genetics, inspired from the biological evolution, survival of the fittest among string structures with a structured yet, randomized information exchange with in the population to form a search algorithm with some of the innovative flair of human search. In every generation a new set of artificial creatures (strings) created using bits and piece of the old, an occasional new part is tried for good measure. Being randomized GAs exploit historical information to speculate on new search points with expecting improved performance. The current literature identifies three main types of search methods or optimization techniques. They are [13]:

(i) Calculus –based method
(ii) Enumerate method
(iii) Random search techniques

Calculus based and enumerative methods are comfortable in their ability to deliver solutions in applications involving search spaces of limited problem domain. Both methods are local in scope, the optima they seek are the best in a neighborhood of the current search point. But in their application to real world of search, which is fraught with discontinuities of functions and their derivatives and vast multi-modal noisy search spaces, they break down on problems of even moderate size and complexity. Their inability and inefficiency to overcome the local optima and reach the global optimum make them insufficiently robust, precluding their application to complex problems as search method.

On the other hand, random search algorithms managed to overcome the inherent disabilities of the calculus and enumerative methods. Yet, random schemes that searches and save the best must also be discounted because of the efficiency requirement. Random searches, in the long run can be expected to do no better than enumerative schemes. In our haste to discount strictly random search methods, we must be careful to separate them from randomized techniques.

The randomized search techniques incorporated the basic advantages of random search but used it only as a tool to guide a more highly exploitative search. In these methods, the search is carried out randomly and information gained from a search is used in guiding the next search. Genetic algorithm is an example of such technique, which drew inspiration from the robustness of nature.

Genetic algorithms in their quest for robustness surpassed their traditional cousins and differ in some very fundamental ways. GAs are different in the following aspects:

(i) GAs work with a coding of the parameter set, not the parameters themselves.
(ii) GAs searches from a population of points, not from a single point as in conventional search algorithms.
(iii) GAs uses objective function information, not derivatives or other auxiliary knowledge.
(iv) GAs use probabilistic tradition rules but not deterministic rules.

In this chapter, Genetic algorithm and its operators have been discussed in detail. The problem of optimal power flow using GA is formulated and the algorithm for OPF using GA is presented up to the level of implementation.

## 4. Results and discussions

The proposed approach has been tested on the standard IEEE 30-bus test system. The cost coefficients of IEEE 30 bus system as shown below tables.

4.1 When fuel cost minimization taken as objective, fuel cost will be reduced but active power losses will be increased.

4.2 When active power loss minimization taken as objective, active power losses will be reduced but fuel cost will be increased.

To reduce both fuel cost and active power losses, both fuel cost and active power losses taken as objective.

4.3 fuel cost and active power loss minimization as objective.

| OBJECTIVE | | WITHOUT TCSC | WITH TCSC |
|---|---|---|---|
| FUEL COST MINIMIZATION | a)fuel cost min | 849.41$/hr | 828.33$/hr |
| | b)active power loss min | 6.483MW | 5.97MW |
| ACTIVE POWER LOSS MINIMIZATION | a)fuel cost min | 1064.7$/hr | 955.84/$hr |
| | b)active power loss min | 4.3285 MW | 3.49 MW |
| BOTH FUEL COST MIN AND ACTIVE POWER LOSS MIN | a)fuel cost min | 872.667 $/hr | 829.40 $/hr |
| | b)active power loss min | 5.725 MW | 5.422 MW |

If both fuel cost and active power loss minimization taken as objective, both will be reduced.

### 5.3.1 Case study (i)-IEEE 30 bus system

The GA parameters are
Population size = 40
Maximum number of generations = 100
Elitism probability = 0.15
Cross over probability = 0.95
Mutation probability = 0.001

Table 1 OPF results for IEEE 30 bus system with fuel cost and active power loss minimization as objective

| Generator bus number | Active power outputs(MW) | Voltage magnitudes(p.u) | Fuel cost ($/hr) |
|---|---|---|---|
| 1 | 110.26 | 1.0180 | 266.10 |
| 2 | 42.81 | 1.0350 | 106.98 |
| 5 | 34.7 | 0.9910 | 109.95 |
| 8 | 29.98 | 1.0227 | 99.30 |
| 11 | 15.66 | 1.0098 | 53.11 |
| 13 | 50.66 | 1.0467 | 216.14 |

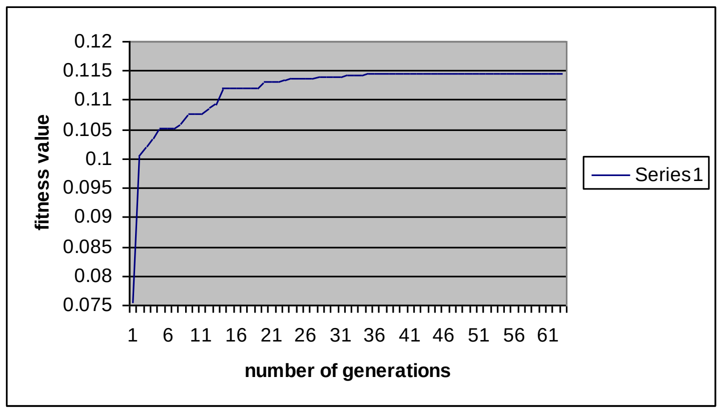


Fig.3.1 Variation of best fitness with number of generations

From the analysis of above results, both fuel cost and active power losses taken as objective, due to the influence of TCSC fuel cost reduced from 872.667$/hr to829.40 $/hr, and active power losses are reduced from 5.7255MW to 5.422 MW.

a) Fuel cost minimization taken as objective, due to the influence of TCSC the fuel cost reduced from 849.41$/hr to 828.332$/hr.
b) Active power loss minimization taken as objective, due to the influence of TCSC the active power losses are reduced from 4.3285MW to 3.4925MW.
c) Both fuel cost and active power losses taken as objective, due to the influence of TCSC fuel cost reduced from 872.667$/hr to 829.40 $/hr, and active power losses are reduced from 5.7255MW to 5.422 MW.

## 5. CONCLUSIONS

In this paper Optimal power flow (OPF) has been solved using genetic algorithm (GA) to obtain the optimal fuel cost and active power losses. To reduce the total fuel cost and active power losses further, OPF has been solved with FACTS device like TCSC.

Case 1: IEEE 30 bus system

- Fuel cost minimization taken as objective, due to the influence of TCSC the fuel cost reduced from 849.41$/hr to828.332$/hr.
- Active power loss minimization taken as objective, due to the influence of TCSC the active power losses are reduced from 4.3285MW to 3.4925MW.
- Both fuel cost and active power losses taken as objective, due to the influence of TCSC fuel cost reduced from 872.667$/hr to829.40 $/hr, and active power losses are reduced from 5.7255MW to 5.422 MW.

## 6 .REFERENCES

[1] Narain G.Hingorani, Laszlo Gyugyi, “Understanding FACTs”, Concepts and technology of Flexible AC Transmission Systems, *IEEE Press*.

[2] M.S.Osman, M.A.Abo-sinna, A.A.Mousa, ``A solution to the optimal power flow using genetic algorithm”, Appl.math.comput.2003.

[3] William D.Rosehart, Claudio A canizares,` `Multi objective optimal power flows to evaluate voltage security costs in power net works” ,IEEE trans. On power systems, vol.18,no2 ,may2003

[4] Anastasios G. Bakirtzis, Pandel N. Biskas, Christoforos E. Zoumas, Vasilios Petridis, ”Optimal Power Flow by Enhanced Genetic Algorithm”, *IEEE Transactions On Power Systems,* Vol. 17, no. 2, pp 229-236, May 2002.

[5] X.-P. Zhang and E. Handschin, “Optimal power flow control by converter based facts controllers,” in *Proc. 7th Int. Conf. AC-DC Power Transm.*, London, U.K., pp 28–30, Nov 2001.

[6] L. L. Lai, J. T. Ma, R. Yokoyama, and M. Zhao, “Improved genetic algorithms for optimal power flow under both normal and contingent operation states,” *Elec. Power Energy Syst.*, Vol. 19, no. 5, pp. 287–292, 1997.

[7] M.Noroozian, G.Anderson, “Power Flow Control by Use of Controllable Series components” IEEE Transactions on Power Delivery, VO1.8, No.3, July 1993, 1420-1428.

[8] ``Allocation of TCSC to optimize total transmission capacity in a competitive power market”, Wang feng student member IEEE, G.B.Shrestha senior member, IEEE.

[9] Optimal choice and allocation of FACTS devices using genetic algorithms. L.j.cai, student member IEEE and Erlich, member IEEE.

 

[10] Optimal location and settings of FACTS for optimal power flow problem using a hybrid/PSO algorithm.M.A. Abido, M.M.Al-Hulail.

[11] G.Shaoyun and T S chung ,optimal power flow incorporating FACTS devices with power flow control constraints

[12] S. Rajasekharan, G.A. Vijayalakshmi pai, “Neural Networks, Fuzzy Logic, and Genetic Algorithms Synthesis and Applications”, Prentice-Hall of India Private limited.

 