On-Line Optimal Power Flow Using Evolutionary Programming Techniques

M.I. Mosaad, M.M. El Metwally, A.A. El Emary and F.M. El Bendary
Lecturer-EEET Department-Yanbu Industrial College,Yanbu Al-Sinaiya, PO Box: 30436
Kingdom of Saudi Arabia
E-mail: m_i_mosaad@hotmail.com

Abstract

This paper aims to solve On-Line Optimal Power Flow (ON-OPF) to minimize fuel cost using Evolutionary Programming Techniques. The solution of that optimization problem is based on using the Particle Swarm Optimization (PSO) technique for each loading condition with minimum fuel cost. All previous obtained results are used as a database for training an Artificial Neural Network (ANN) to obtain an on line solution (decision) to control output power of each generating unit at different loading conditions while satisfying minimum fuel cost.

Keywords: On-Line Optimal Power Flow, Particle Swarm Optimization and Artificial Neural Network

1. Introduction

Throughout the entire world, the electric power industry has undergone a considerable change in the past decade and will continue to do so for the next several decades. In the past, the electric power industry has been either a government-controlled or a government-regulated Industry which existed as a monopoly in its service region. All people, businesses, and industries were required to purchase their power from the local monopolistic power company. This was not only a legal requirement, but a physical engineering requirement as well. It just did not appear feasible to duplicate the resources required to connect everyone to the power grid. Over the past decade, however, countries have begun to split up these monopolies in favor of the free market [1 -3].

Optimal Power Flow (OPF) solution methods have been developed over the years to meet this very practical requirement of power system operation [4-7].The optimal power flow problem has been discussed since its introduction by Carpentier [8]. Because the OPF is a very large, non-linear mathematical programming problem, it has taken decades to develop efficient algorithms for its solution. Many different mathematical techniques have been employed for its solution.

The majority of the techniques discussed in the literature use one of the following five methods [9-12]:

1. Lambda iteration method, also called the equal incremental cost criterion (EICC) method.
2. Gradient method.
3. Newton’s method.
4. Linear programming method.
5. Interior point method.

There are many uncertainties in power system problems, because power systems are large, complex, and geographically widely distributed. More recently, deregulation of power utilities has introduced new issues into the existing problems. It is desirable that solutions of power system problems should be optimum globally, but solutions searched by mathematical optimization methods used are normally optimum locally. These facts make it difficult to deal effectively with many power system problems through strict mathematical formulation alone. Therefore stochastic search techniques such as simulated annealing (SA), Genetic Algorithms (GAs) Particle Swarm optimization, (PSO) and (ANN) are being used to find global or near global optimal solutions. Although these methods have been employed to solve complex nonlinear OPF problems, they do not always guarantee a globally optimal solution, but they provide a reasonable solution in a short computation time.

A network flow algorithm to solve multiple area OPF with tie line constrains was proposed by [13]. Adaptive Hopfield Neural Network has been applied to solve OPF problem with piecewise quadratic cost function [14]. GAs with fuzzy logic controllers to adjust crossover, and mutation probabilities to solve combined environmental economic dispatch, have been applied [15].

With different loading conditions, different OPF solutions using PSO are obtained. ANN database is formed with these load values to be the input to the network and the output power of each generator is the output of that network while satisfying OPF. In this way, the results of the economic and control operations of the ON-OPF can easily be implemented in the network.

2. Problem Formulation

Optimization of the generating fuel cost can be described as:

The objective function F is to determine the generation levels and the interchange power between each generating unit while satisfying a set of constrains as:

$$\text{Min(F)} = \text{Min} \sum_{n=1}^{N} f_n(P_n) \tag{1}$$

Where $f_n(P_n)$ is the fuel cost (operation cost) of unit n, in terms of active power generated by this unit, P_n, and N is the number of generators in the system.
The cost function of the fuel cost has been approximated as a quadratic function given as:

$$f_n(P_n) = a_n P_n^2 + b_n P_n + c_n \tag{2}$$

Where a_n, b_n and c_n are the fuel cost coefficients in \$/MW^2 per hr, \$/MW per hr and \$ per hr, respectively, and are given in Appendix 1.
Subjected to the following constrains:
i-Power balance constraint:

$$\sum_{n=1}^{N} f_n(P_n) = P_D + \sum_{k=1}^{K} P_{lk} \tag{3}$$

Where P_{lk} are the transmission line losses and k is the number of the lines in the system
ii-Generation active power constraint:

$$P_{n_{\min}} \le P_n \le P_{n_{\max}} \tag{4}$$

iii-Generation reactive power constraint:

$$Q_{n_{\min}} \le Q_n \le Q_{n_{\max}} \tag{5}$$

Where Qn is the reactive power at each generation unit n
iv-Line limits constraint:

$$I_{k\min} \le I_k \le I_{k\max} \tag{6}$$

Where I_k is the current at each line k .
v- Bus voltage constraint

$$V_{\min} \le V \le V_{\max} \tag{7}$$

Where V is the voltage magnitude at each bus .

3. Optimization Algorithems

OPF is a tool used for both the operation and planning of a power system. There are different methods to solve OPF problems. Heuristic methods may be used to solve combinatorial optimization problems. These methods are called “intelligent,” because the move from one solution to another is done using rules close to human reasoning. The heuristic algorithms search for a solution inside a subspace of the total search space. Thus, they are able to give a good solution of a certain problem in a reasonable computation time, but they are not assured to reach the global optimum. The most important advantage of heuristic methods lies in the fact that they are not limited by restrictive assumptions about the search space like continuity, existance of derivative of objective function, etc.

Several heuristic methods exist. Among them, we may quote Tabu Search method (TS) [16], Simulated Annealing (SA) [17], Genetic Algorithms (GAs) [18], and Particle Swarm Optimization (PSO) algorithms [19]. Each one has its own properties and drawbacks. The TS is basically a deterministic method, and experience shows that no random process might restrict the search in the set of solutions. The SA needs long computation time. Further, there are an important number of parameters that are difficult to determine, such as the cooling schedule.

In this research PSO algorithm is used to achieve OPF solution of power system with different load conditions. ANN database is formed with results obtained from PSO to achieve ON-OPF.

Particle Swarm Optimization Techniques

In 1995, Kennedy and Eberhart first introduced the PSO algorithm [20], motivated by social behavior of organisms such as fish schooling and bird flocking. PSO, as an optimization tool, provides a population-based search procedure in which individuals called particles change their positions (states) with time. The basic assumption behind the PSO algorithm is birds find food by flocking and not individually.

This leads to the assumption that information is owned jointly during flocking. Basically, PSO was developed for two-dimension solution space [20].

Let x and y denote a particle coordinates (position) and its corresponding flight speed (velocity) V_x in the x direction and V_y in the y direction. Modification of the individual position is realized by velocity and position information.

PSO algorithm for N-dimensional problem formulation can be described as follows. Let P be the particle position and V is the velocity in a search space.

Consider i as a particle in the total population (swarm).The i^{th} particle position can be represented as P_i= (P_{i1}, Pi2, P_{i3}, P_{iN}) in the N-dimensional space. The best previous position of the i^{th} particle is recorded and represented as:
P_{besti}= (P_{besti1}, P_{besti2}, P_{besti3},…..P_{bestij}).

The index of the best particle among all the particles in the group is represented by g_{best}. The velocity i^{th} particle is represented as $V_i = (V_{i1}, V_{i2}, V_{i3},.....V_{ij})$.

The modified velocity and position of each particle can be calculated using the current velocity and the distance from P_{best} to g_{best} as indicated in following formulas:

$$V_{ij}^{(t+1)} = w * V_{ij}^{(t)} + c_1 * rand_1 * (Pbest_{ij} - Pbest_{ij}^{(t)}) + c_2 * rand_2 * (gbest_i - Pbest_{ij}^{(t)}) \quad (8)$$

$$p_{ij}^{(t+1)} = p_{ij}^{(t)} + v_{ij}^{(t+1)} \quad (9)$$

$i = 1,2,.......I$ and $j = 1,2,.......N$

Where

N	number of dimensions in a particle.
I	number of particles.
W	inertia weight factor.

T	pointer of iterations.
c_1, c_2	accelerating constant.
$rand_1$,$rand_2$	are uniform random values in the range of [0,1].
$v_{ij}^{(t)}$	velocity of the j^{th} dimension in the i^{th} particle.
$p_{ij}^{(t)}$	current position of the j^{th} dimension in the i^{th} particle at iteration t.

Inertia weighting factor w has provided improved performance when using linearly decreasing [19]. Its value decreases linearly from about 0.9 to 0.4 during a run. Suitable selection of w provides a balance between global and local exploration and exploitation, and results in fewer iterations on average to find a sufficiently optimal solution. Its value is set according to the following equation:

$$w = w_{max} - \frac{w_{max} - w_{min}}{t_{max}} * t \qquad (10)$$

Where

w_{max} and w_{min}	are both random numbers called initial and final weights respectively
t_{max}	maximum number of ite-rations .
t	the current iteration number.

In equation (8), the first term indicates the current velocity of the particle, and the second term represents the cognitive part of PSO where the particle changes its velocity based on its own thinking and memory. The third term represents the social part of PSO where the particle changes its velocity based on the social-psychological adaptation of knowledge [20].

4. Development of the Proposed Methods

In this paper, the process of determining the generation levels and the interchange power between each generating unit in order to minimize the overall generating cost using PSO, is developed to obtain efficiently a high quality solution, within practical power system operation.

Implementation of PSO Algorithm in OPF Problem

In this paper the solution to ED using PSO algorithm is introduced. The PSO algorithm is utilized mainly to determine the optimal generation power of each unit, to minimize the total generation cost. Its implementation consists of the following six steps:

Step1 Specify the number of generating units as the dimension. The particles are randomly generated between the maximum and minimum limits of the generators. If there are N units, the i^{th} particle is represented as follows: $P_i = (P_{i1}, P_{i2}, P_{i3} \ldots P_{iN})$.

Step2 The particles velocities are generated randomly in the range of $[-v_j^{max}, v_j^{max}]$

The maximum velocity limit is set at 10-20 % of the dynamic range of the variables on each dimension [17, 21].

Step3 Objective function values of the particles are evaluated using equation (1).These determined values are set as P_{best} value of the particles.

Step4 The best value among all the P_{best} values is identified and denoted as g_{best}.

Step5 New velocities for all the dimensions in each particle are calculated using equation (8). Then the position of each particle is updated using equation (9).

Step6 The objective function values are calculated for the updated positions of the particles. If the new value is better than the previous P_{best}, the new value is set to P_{best}, If the stopping criteria are met, the positions of particles represented by g_{best} are the optimal solution, otherwise the procedure is repeated from step 4.

Artificial Neural Network

ANN is considered as a relatively new information processing technique. It can be defined as a computing system made up of a number of simple, highly interconnected processing elements, which process information by its dynamic state response. A neural network consists of a number of very simple and highly interconnected processors called neurons, which are the analogs of the neurons in the brain [22]. The neurons are connected by a large number of weighted links, over which signals can pass [23]. In the present application, a three- layer neural network (having an input layer, a hidden layer and an output layer) has been used, together with a tansigmoidal activation function and supervised training via a back-propagation technique. The well known enhancement of introducing a momentum term in the weight updating formula has also been successfully applied to reduce training times and to help in avoiding premature convergence.

The weights of the neural network are adapted depending on the error signal coming from the difference between desired and actual output power of each generator. To optimize the network, its error function is formulated in such a way that it is quadratic in terms of the parameters to be estimated.

The error function E is defined as:

$$E = \frac{1}{2}\sum\left(p_r(m) - p_L(m)\right)^2 = \frac{1}{2}\sum \overline{e(m)}^2 \qquad (11)$$

Where p_r is the actual output power and p_L is the desired target at any time k. During each time interval from m-1 to m, the back-propagation algorithm is used to update the connective weights w according to the relation:

$$w_{ij}(n+1) = w_{ij}(n) - \lambda\frac{\partial E}{\partial w_{ij}(n)} + \mu\,\Delta w_{ij}(n-1) \qquad (12)$$

Where λ is the learning rate, μ is the momentum factor, and n indicates the number of training iterations. A three-layer (input, hidden, and output) network is used for the neural controller.

5. Simulation Results

Solutions for OPF problem were obtained for IEEE 14 bus system using PSO for each loading conditions.

For implementing PSO method in the OPF problem, the population size of 100 was taken and the maximum number of generations was taken as 100. The inertia weight factor is set by (10), where w_{max} and w_{min} are 0.9 and 0.2, respectively. Acceleration constants c1, c2 are assumed to be equal (c1= c2 =2).

IEEE 14 bus system

In this case an IEEE 14 bus system containing three generating units, eleven loads and sixteen lines are shown in Figure 1. The cost coefficients of the three generating units are given in Appendix 1.

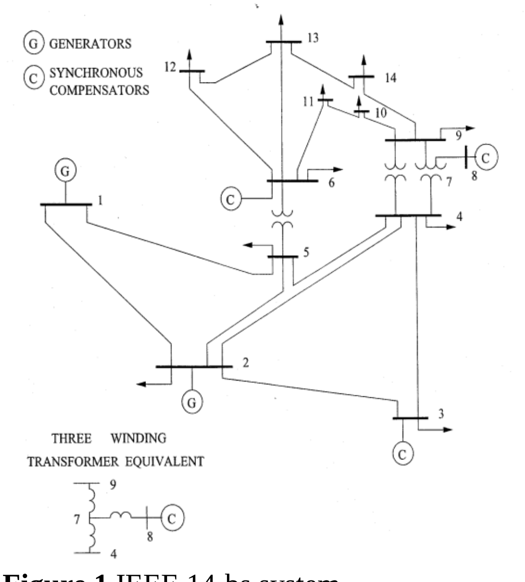

Figure 1 IEEE 14-bs system

Case 1: Conventional case, the total load of the system is 259 MW, and the loading conditions for this case are given in Table 1. Table 2 depicts the output power of each generator, while satisfying OPF.

Table 1. IEEE 14 bus system loading data

Bus #	P (MW)	Q (MVAr)
2	21.7	12.7
3	94.2	19.0
4	47.8	4.0
5	7.6	1.6
6	11.2	7.5
9	29.5	16.6
10	9.0	5.8
11	3.5	1.8
12	6.1	1.6
13	13.5	5.8
14	14.9	5.0

Table 2. Simulation results of OPF using PSO for IEEE 14 bus system (1st case).

Generating Unit	Pg (MW)
G1	185.3
G2	35.22
G3	46.41

Case 2 **:** Increase the active load power P at buses # 2, 3, 4 and 5 by 10% . Table 3 depicts the output power of each generator, while satisfying OPF.

Table 3. Simulation results of OPF using PSO for IEEE 14 bus system (2nd case).

Generating Unit	Pg (MW)
G1	190.971
G2	40.94
G3	52.77

Case 3**:** Decrease the active load power P at buses # 2, 3, 4 and 5 by 10% .Table 4 depicts the output power of each generator, while satisfying OPF.

Table 4. Simulation results of OPF using PSO for IEEE 14 bus system (3rd case).

Generating Unit	Pg (MW)
G1	179.6764
G2	29.4998
G3	40.089

Case 4**:** Increase the load active and reactive power P at buses #6, 9, 10, 11, 12, 13 and 14 by 10%. Table 5 depicts the output power of each generator, while satisfying OPF.

Table 5. Simulation results of OPF using PSO for IEEE 14 bus system (4th case).

Generating Unit	Pg (MW)
G1	188.5552
G2	38.3778
G3	49.26

Case 5**:** Decrease the load active and reactive power P at buses #6, 9, 10, 11, 12, 13 and 14 by 10%. Table 6 depicts the output power of each generator, while satisfying OPF.

Table 6. Simulation results of OPF using PSO for IEEE 14 bus system (5th case).

Generating Unit	Pg (MW)
G1	182.1124
G2	32.0768
G3	43.5846

Case 6: Decrease the load active and reactive power P at buses #2, 3, 4, 5, 6, 9, 10, 11, 12, 13 and 14 by 10% .Table 7 depicts the output power of each generator, while satisfying OPF.

Table 7. Simulation results of OPF using PSO for IEEE 14 bus system (6^{th} case)

Generating Unit	Pg (MW)
G1	176.46
G2	26.3616
G3	37.2643

Using the results obtained from cases one to six to be the training data of the neural network with eleven inputs (loads) and three outputs (generated power) .

The number of units of hidden layer is eight units. The number of output units of neural controller is three units, that control generation level of each generator of the system in order to handle ON-OPF .

The parameters used in this case are error is $2e^{-8}$% of the load power, and the maximum epochs for training are set to be 4000.

Tables from 8-10 depicts the difference between actual output power (desired) and output power obtained from NN training and the error of each one in six loading cases for the three generated power.

Table 8. Actual output power and trained power for generator #1.

Loading Cases	P1 actual	P1 Train	Abs (Error) %
1	185.3	185.647	0.1873
2	190.971	189.750	0.6394
3	179.676	180.063	0.2154
4	188.555	188.173	2026.0
5	182.112	182.825	0.3915
6	185.3	185.647	0.1873

Table 9. Actual output power and trained power for generator #2.

Loading Cases	P2 Actual	P2 Trained	Abs (Error) %
1	35.22	35.4246	0.5809
2	40.94	38.9749	4.8000
3	29.4998	31.0191	5.1502
4	3778.38	38.9964	1.6119
5	32.0768	31.4965	1.8091
6	35.22	35.4246	0.5809

Table 10. Actual output power and trained power for generator #3.

Loading Cases	P3 actual	P3 Trained	Abs (Error) %
1	46.41	47.1665	1.6300
2	52.77	52.6651	0.1988
3	40.089	4818.39	1.5146
4	49.26	49.6995	0.8922
5	43.5846	44.3983	1.8669
6	46.41	47.1665	1.6300

6. Conclusions

In this paper, we have successfully employed PSO and ANN methods to solve the ON-OPF problem with the power flow constraints. Fuel cost function has been approximated as a quadratic function. Results showed that PSO methods are well suited for obtaining the best solutions for fuel cost functions of differentiable, non-smooth, and non-differentiable functions of the test system. Training ANN used in this paper has taken a long time but this is performed off-line. When implementing this network in a real system, it gives fast response time on-line.

7. Appendix

Fuel cost coefficients of IEEE 14 bus system.

Generator	A	B	C
1	0.0050	1.89	150
2	0.0055	3.5	115
3	0.0060	3.5	40

8. References

[1] B. R. Barkovich and D. Hawk, Charting a New Course in California, IEEE Spectrum, Vol. 33, No. 7, July 1996, pp. 26-31.

[2] M. G. Morgan and S. Talukdar, Nurturing R&D, IEEE Spectrum, Vol. 33, No.7, July 1996, pp. 32-33.

[3] H. Rudnick, Pioneering Electricity Reform in South America, IEEE Spectrum, Vol. 33, No. 8, August 1996, pp. 38-44.

[4] Acha, E., Ambriz-Pe´rez, H., Fuerte-Esquivel, C.R., Advanced Transformer Control Modelling in An Optimal Power Flow Using Newton’s Method, IEEE Trans. Power Systems 15(1), pp. 290–298, 2000.

[5] Huneault, M., Galiana, F.D., A Survey of the Optimal Power Flow Literature, IEEE Trans. Power Systems 6(2), pp. 762–770, 1991.

[6] Monticelli, A., Liu,W.H.E., Adaptive Movement Penalty Method for the Newton Optimal Power Flow, IEEE Trans. Power Systems,Vol.7(1), pp. 334–342, 1992.

[7] El-Hawary, M.E., Tsang, D.H., The Hydro-Thermal Optimal Power Flow, A Practical Formulation and Solution Technique Using Newton’s Approach, IEEE Trans. Power Systems PWRS-1(3), pp. 157–167, 1986.

[8] J. Carpienter, Contribution e l’étude do Dispatching Economique, Bulletin Society Française Electriciens, Vol. 3, August 1962.

[9] J. Wood and B. F. Wollenberg, Power Generation Operation and Control, New York, NY: John Wiley & Sons, Inc., pp. 39-517, 1996.

[10] H.W .Dommel and W. F. Tinney, Optimal Power Flow Solutions, IEEE Transactions on Power Apparatus and Systems, Vol. PAS-87, October 1968, pp. 1866-1876.

[11] D. I. Sun, B. Ashley, B. Brewer, A. Hughes and W. F. Tinney, Optimal Power Flow by Newton Approach, IEEE Transactions on Power Apparatus and Systems, Vol. PAS-103, October 1984, pp. 2864-2880.

[12] O. Alsac, J. Bright, M. Prais and B. Stott, Further Developments in LP-Based Optimal Power Flow, IEEE Transactions on Power Systems, Vol. 5(3), pp. 697-711, 1990.

[13] Streiffert Dan. Multiple Area Economic Dispatch with Line Constrains, IEEE Transactions on Power Systems, Vol. 10(4), pp. 1946-1951, 1995.

[14] Lee KY, Yome AS, Park JH, Adaptive Hopfield Neural Network For Economic Load Dispatch, IEEE

Transactions on Power Systems, 13(2), pp. 519-526, 1998.

[15] Song YH, Wang PV, Johns AT., Environmental Economic Dispatch Using Fuzzy Logic Controller Genetic Algorithms, IEE Proc. Gener. Transm. Distr., Vol. 144(4), pp. 377-382, 1997.

[16] F. Glover, Tabu Search, University of Colorado, Boulder, CAAI Report, pp. 88-93, 1988.

[17] S. Kirkpatrick, C. D. Gellat, and M. P. Vecchi, Optimization by Simulated Annealing, Science, Vol. 220, pp. 671–680, 1983.

[18] D. E. Goldberg, Genetic Algorithms in Search Optimization and Machine Learning, Addison-Wesley Publishing Company, Inc., 1989.

[19] Z. L. Gaing, Particle Swarm Optimization to Solving the Economic Dispatch Considering the Generator Constraints, IEEE Transactions on Power Systems, Vol. 18(3), pp. 1187-1195, 2003.

[20] J. Kennedy and R. Eberhart, Particle swarm optimization, Proc. IEEE Int. Conf. Neural Networks, Vol. IV, pp. 1942–1948, 1995.

[21] M.M. El Metwally, A.A. El Emary, F.M. El Bendary and M.I. Mosaad ,Optimal Power Flow Using Evolutionary Programming Techniques, MEPCON’2008 Power Sys., pp. 260-264, 2008.

[22] Yao Zhang, Pratyush Sen, and Grant E. Hearn, An On-Line Trained Adaptive Neural Controller, IEEE Control System Magazine, pp. 67-75, Oct., 1995.

[23] G.M. Hashem, A.Y. Abdelaziz, Neuralnetwork Based Estimation of Single-Phase Converter Performance Parameters, MEPCON’ 2003 Ind. Electron, pp. 635-641.