

# Economic Power Dispatch of Power Systems with a NO<sub>x</sub> emission Control via an Evolutionary Algorithm

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*Abstract:* - This paper presents solution of optimal power flow (OPF) problem of medium-sized power systems via a genetic algorithm of real type. The objective is to minimize the total fuel cost of generation and environmental pollution caused by fossil based thermal generating units and also maintain an acceptable system performance in terms of limits on generator real and reactive power outputs, bus voltages, shunt capacitors/reactors, transformers tap-setting and power flow of transmission lines. CPU times can be reduced by decomposing the optimization constraints of the power system to active constraints manipulated directly by the genetic algorithm, and passive constraints maintained in their soft limits using a conventional constraint load flow. Simulation results on the IEEE 30-bus network with 6 generators show that by this method, an optimum solution can be given quickly. Further analyses indicate that this method is effective for medium-scale power systems.

*Key-Words:* - Optimal Power Flow, Power Systems, Pollution Control, NO<sub>x</sub> emission and evolutionary algorithm

## 1 Introduction

The optimal power flow calculation optimizes the static operating condition of a power generation-transmission system. The main benefits of optimal power flow are (i) to ensure static security of quality of service by imposing limits on generation-transmission system's operation, (ii) to optimize reactive-power/voltage shedeluling and (iii) to improve economy of operation through the full utilization of the system's feasible operating range and by the accurate coordination of transmission losses in scheduling process. The OPF has been usually considered as the minimisation of an objective function representing the generation cost and/or the transmission loss. The constraints involved are the physical laws governing the power generation-transmission systems and the operating limitations of the equipment.

The optimal power flow has been frequently solved using classical optimisation methods. Effective optimal power flow is limited by (i) the high dimensionality of power systems and (ii) the incomplete domain dependent knowledge of power system engineers.

The first limitation is addressed by numerical optimisation procedures based on successive linearization using the first and the second derivatives of objective functions and their constraints as the search directions or by linear programming solutions to imprecise models [1-4]. The advantages of such methods are in their mathematical underpinnings, but disadvantages exist also in the sensitivity to problem formulation, algorithm selection and usually converge to local minima [5].

The second limitation, incomplete domain knowledge, precludes also the reliable use of expert systems where rule completeness is not possible.

As modern electrical power systems become more complex, planning, operation and control of such systems using conventional methods face increasing difficulties. Intelligent systems have been developed and applied for solving problems in such complex power systems.

In recent years, environmental constraint started to be considered as part of electric system planning. That is, minimization of pollution emission (NO<sub>x</sub>, SO<sub>x</sub>, CO<sub>2</sub>, etc.) in case of thermal generation power plants. However, it became necessary for power utilities to count this constraint as one of the main objectives, which should be solved together with the cost problem. Thus, we are facing with a multi-objective problem to deal with.

Reference [6] solves the economic load dispatch under environmental restrictions in a multi-hour time horizon minimizing fuel consumption cost for SO<sub>2</sub> and NO<sub>x</sub> using an emission ton limit for the first one and an emission rate for the second one.

Reference [7] solves a cost minimization problem proposing a solution via quadratic programming, where environmental restrictions are modeled with lineal inequalities.

In a previous article [8], the authors have proposed the use of GA in binary code on the optimal power flow problem using as objective function the minimization of only fuel cost in its quadratic form. This paper describes

the solution of the optimal power flow problem with objective function on the fuel cost and NOx emission control. The second part of the objective function is modeled as the sum of quadratic and exponential functions of generator active power output [9]. Because the total objective function is very non-linear, a genetic algorithm with real coding of control parameters is chosen in this work in order to well taking into account this nonlinearity and to converge rapidly to the global optimum.

To accelerate the processes of the optimisation, the controllable variables are decomposed to active constraints and passive constraints. The active constraints which influence directly the cost function are included in the (GA or EP) process. The passive constraints which affect indirectly this function are maintained in their soft limits using a conventional constraint load flow, only, one time after the convergence of GA or EP. The search of the optimal parameters set is performed taking into the account that the power losses are 2% of the power demand. The slack bus parameter will be recalculated in the load flow process to take the effect of the passive constraints and the exact power losses.

The algorithm was developed in an Object Oriented fashion, in the C++ programming language. This option was made given the high flexibility and ease of reconfiguration given by this approach [10].

## 2 Problem formulation

The standard OPF problem can be written in the following form,

$$\begin{aligned} & \text{Minimise } F(x) && \text{(the objective function)} \\ & \text{subject to : } h(x) = 0 && \text{(equality constraints)} \\ & \text{and } g(x) \leq 0 && \text{(inequality constraints)} \end{aligned}$$

where  $x$  is the vector of the control variables, that is those which can be varied by a control center operator (generated active and reactive powers, generation bus voltage magnitudes, transformers taps etc.);

The essence of the optimal power flow problem resides in reducing the objective function and simultaneously satisfying the load flow equations (equality constraints) without violating the inequality constraints

### 2.1 Objective Function

#### 2.1.1 Economic objective function

The most commonly used objective in the OPF problem formulation is the minimisation of the total operation cost of the fuel consumed for producing electric power within a schedule time interval (one hour). The individual costs of each generating unit are assumed to be function, only, of active power generation and are represented by quadratic curves of second order. The objective function for the entire power system can then

be expressed as the sum of the quadratic cost model at each generator.

$$F_{EC}(x) = \sum_{i=1}^{ng} (a_i + b_i P_{g_i} + c_i P_{g_i}^2) \quad \$/\text{h} \quad (1)$$

where  $ng$  is the number of thermal units including the generator at the slack bus,  $P_{g_i}$  is the generated active power at bus  $i$  and  $a_i$ ,  $b_i$  and  $c_i$  are the unit costs curve for  $i^{\text{th}}$  generator.

#### 2.1.2 Emission objective function

In a power generating system containing fossilfuel units, the total emission can be reduced by minimizing the three major pollutants oxides of nitrogen (NOx), oxides of sulfur (SOx) and carbon dioxide (CO<sub>2</sub>). The objective function that minimizes the total emissions can be expressed in a linear equation [11] as the sum of all the three pollutants (in tons/MWh) resulting from generation  $P_{g_i}$  of the  $i^{\text{th}}$  generator.

In this study, Nitrogen-Oxid (NOx) emission is taken as the index from the viewpoint of environment conservation. The amount of NOx emission is given as a function of generator output (in Ton/hr), that is, the sum of quadratic and exponential functions [12] of generator active power output as

$$F_{PL} = \sum_{i=1}^{ng} (a_i + b_i P_{g_i} + c_i P_{g_i}^2 + d_i \exp(e_i P_{g_i})) \quad (2)$$

where  $a_i$ ,  $b_i$ ,  $c_i$ ,  $d_i$ , and  $e_i$  are the pollution coefficients of the  $i^{\text{th}}$  generating unit.

The pollution control can be obtained by assigning a cost factor to the pollution level expressed as

$$F_{PC} = F_{ECC} \cdot \sum_{i=1}^{ng} (a_i + b_i P_{g_i} + c_i P_{g_i}^2 + d_i \exp(e_i P_{g_i})) \quad (3)$$

where,  $F_{ECC}$  is the emission control cost factor in \$/Ton which was taken as 550.66 \$/Ton [13].

#### 2.1.3 Total objective function

The total objective function considers at the same time the cost of the generation and the cost of pollution level control. These objectives have complicated natures and are conflicted in some points (the minimization of the generation cost can maximizes the emission cost and vice versa); therefore a compromised technique is required. Consequently, the total cost (in \$/hr) is expressed as [14]

$$F = \alpha \cdot F_{PC} + (1 - \alpha) \cdot F_{GC} \quad (4)$$

where  $\alpha$  is a compromise factor varied in the range  $0 \leq \alpha \leq 1$ . The boundary values  $\alpha=1$  and  $\alpha=0$  give the conditions for the pure minimization of the fuel cost function and the pure minimization of the pollution control level.

## 2.2 Types of equality constraints

While minimizing the objective function, it is necessary to make sure that the generation still supplies the load demands plus losses in transmission lines. Usually the power flow equations are used as equality constraints.

$$\begin{bmatrix} \Delta P_i \\ \Delta Q_i \end{bmatrix} = \begin{bmatrix} P_i(V, \theta) - (Pg_i - Pd_i) \\ Q_i(V, \theta) - (Qg_i - Qd_i) \end{bmatrix} = 0 \quad (5)$$

where active and reactive power injection at bus  $i$  are defined in the following equation:

$$\begin{aligned} P_i(V, \theta) &= \sum_{j=1}^{nbus} V_i V_j (g_{ij} \cos \theta_{ij} + b_{ij} \sin \theta_{ij}), \\ Q_i(V, \theta) &= \sum_{j=1}^{nbus} V_i V_j (g_{ij} \sin \theta_{ij} - b_{ij} \cos \theta_{ij}), \end{aligned} \quad (6)$$

## 2.3 Types of inequality constraints

The inequality constraints of the OPF reflect the limits on physical devices in the power system as well as the limits created to ensure system security. The most usual types of inequality constraints are upper bus voltage limits at generations and load buses, lower bus voltage limits at load buses, var. limits at generation buses, maximum active power limits corresponding to lower limits at some generators, maximum line loading limits and limits on tap setting of TCULs and phase shifter.

The inequality constraints on the problem variables considered include:

- Upper and lower bounds on the active generations at generator buses  $Pg_i^{min} \leq Pg_i \leq Pg_i^{max}$ ,  $i = 1, ng$ .
- Upper and lower bounds on the reactive power generations at generator buses and reactive power injection at buses with VAR compensation  $Qg_i^{min} \leq Qg_i \leq Qg_i^{max}$ ,  $i = 1, npv$
- Upper and lower bounds on the voltage magnitude at the all buses.  $V_i^{min} \leq V_i \leq V_i^{max}$ ,  $i = 1, nbus$ .
- Upper and lower bounds on the bus voltage phase angles  $\theta_i^{min} \leq \theta_i \leq \theta_i^{max}$ ,  $i = 1, nbus$ .
- Upper and lower bounds on the bus voltage phase angles  $\theta_i^{min} \leq \theta_i \leq \theta_i^{max}$ ,  $i = 1, nbus$ .
- Upper and lower bounds on branch MW/MVAR/MVA flows

It can be seen that the generalised objective function  $F$  is a non-linear, the number of the equality and inequality constraints increase with the size of the power distribution systems. Applications of a conventional optimisation technique such as the gradient-based algorithms to a large power distribution system with a very non-linear objective functions and great number of constraints are not good enough to solve this problem. Because it depend on the existence of the first and the second derivatives of the objective function and on the well computing of these derivative in large search space.

## 3 Evolutionary Algorithms in Economic Power Dispatch

Evolutionary algorithms (EAs) are computer-based problem solving systems which are computational models of evolutionary processes as key elements in their design and implementation. Genetic algorithm is the most popular and widely used of all evolutionary algorithms. It transforms a set (population) of individual mathematical objects (usually fixed length character or binary strings), each with an associated fitness value, into a new population (next generation) using genetic operations similar to the corresponding operations of genetics in nature. GAs seem to perform a global search on the solution space of a given problem domain [15-18].

There are three major advantages of using genetic algorithms for optimization problems.

- GAs do not involve many mathematical assumptions about the problems to be solved. Due to their evolutionary nature, genetic algorithms will search for solutions without regard for the specific inner structure of the problem. GAs can handle any kind of objective functions and any kind of constraints, linear or nonlinear, defined on discrete, continuous, or mixed search spaces.
- The ergodicity of evolution operators makes GAs effective at performing global search. The traditional approaches perform local search by a convergent stepwise procedure, which compares the values of nearby points and moves to the relative optimal points. Global optima can be found only if the problem possesses certain convexity properties that essentially guarantee that any local optimum is a global optimum.
- GAs provide a great flexibility to hybridise with domain-dependent heuristics to make an efficient implementation for a specific problem.

Usually there are only two main components of most genetic algorithms that are problem dependent: the problem encoding and the evaluation function.

The problem to be solved by a genetic algorithm is encoded as two distinct parts: the genotype called the chromosome and the phenotype called the fitness function. In computing terms the fitness function is a subroutine representing the given problem or the problem domain knowledge while the chromosome refers to the parameters of this fitness function. Most users of genetic algorithms typically are concerned with problems that are nonlinear.

The traditional binary representation used for the genetic algorithms creates some difficulties for the optimisation problems of large size with high numeric precision. According to the problem, the resolution of the algorithm can be expensive in time. The crossover and the mutation can be not adapted. For such problems, the genetic algorithms based on binary representations have poor performance. The first assumption that is

typically made is that the variables representing parameters can be represented by bit strings. This means that the variables are discretized in an a priori fashion, and that the range of the discretization corresponds to some power of 2. For example, with 10 bits per parameter, we obtain a range with 1024 discrete values. If the parameters are actually continuous then this discretization is not a particular problem. This assumes, of course, that the discretization provides enough resolution to make it possible to adjust the output with the desired level of precision. It also assumes that the discretization is in some sense representative of the underlying function.

Therefore one can say that a more natural representation of the problem offers more efficient solutions. Then one of the greater improvements consists in the use of real numbers directly. Evolutionary Programming algorithms in Economic Power Dispatch provide an edge over common GA mainly because they do not require any special coding of individuals. In this case, since the desired outcome is the operating point of each of the dispatched generators (a real number), each of the individuals can be directly presented as a set of real numbers, each one being the produced power of the generator it concerns.

Our Evolutionary programming is based on the completed Genocop III system [19], developed by Michalewicz, Z. and Nazhiyath, G. Genecop III for constrained numerical optimization (nonlinear constraints) is based on repair algorithms. Genecop III incorporates the original Genecop system [20] (which handles linear constraints only), but also extends it by maintaining two separate populations, where a development in one population influences evaluations of individuals in the other population. The first population  $P_s$  consists of so-called search points which satisfy linear constraints of the problem; the feasibility (in the sense of linear constraints) of these points is maintained by specialized operators (as in Genecop). The second population,  $P_r$ , consists of fully feasible reference points. These reference points, being feasible, are evaluated directly by the objective function, whereas search points are "repaired" for evaluation.

### 3.1 The Original GENECOP System

The Genecop (for GENetic algorithm for Numerical Optimization of Constrained Problem) system [20] assumes linear constraints only and a feasible starting point (a feasible population).

#### 3.1.1 Initialisation

Let  $Pg^k = [Pg_1^k, \dots, Pg_i^k, \dots, Pg_{ng}^k]$  be the trial vector that presents the  $k^{th}$  individual,  $k=1,2,\dots,P$ , of the population to be evolved, where  $I$  is the population size.

The elements of the  $Pg_i$  are the desired values of the power outputs of generators. The initial parent trial vectors  $Pg^k$ ,  $k=1,\dots,P$ , are generated randomly from a reasonable range in each dimension by setting the elements of  $Pg^k$  as

$$Pg_i^k = U(Pg_{i,\min}, Pg_{i,\max}) \text{ for } i=1,2,\dots,ng, \quad (7)$$

where  $U(Pg_{i,\min}, Pg_{i,\max})$  denotes the outcome of a uniformly distributed random variable ranging over the given lower bounded value and upper bounded values of the active power outputs of generators.

A closed set of operators maintains feasibility of solutions. For example, when a particular component  $x_i$  of a solution vector  $X$  is mutated, the system determines its current domain  $dom(x_i)$  (which is a function of linear constraints and remaining value of the solution vector  $X$ ) and the new value  $x_i$  is taken from this domain (either with flat probability distribution for uniform mutation, or other probability distributions for non-uniform and boundary mutations). In any case the offspring solution vector is always feasible. Similarly, arithmetic crossover,  $aX+(1-a)Y$ , of two feasible solution vectors  $X$  and  $Y$  yields always a feasible solution (for  $0 \leq a \leq 1$ ) in convex search spaces.

#### 3.1.2 Offspring Creation

By adding a Gaussian random variation with zero mean, a standard derivation with zero mean and a standard derivation proportional to the fitness value of the parent trial solution, each parent  $Pg^k$ ,  $k=1,\dots,P$ , creates an offspring vector,  $Pg^{k+1}$ , that is,

$$Pg^{k+1} = Pg^k + N(0, \sigma_k^2), \quad (8)$$

where  $N(0, \sigma_k^2)$  designates a vector of Gaussian random variables with mean zero and standard deviation  $\sigma_k$ , which is given according to

$$\sigma_k = r \times \frac{F}{F_{\min}} (Pg_{i,\min} - Pg_{i,\max}) + M, \quad (9)$$

where  $F$  is the objective function value to be minimized in (2) associated with the control vector;  $F_{\min}$  represents the minimum objective function value among the trial solution;  $r$  is a scaling factor; and  $M$  indicates an offset.

#### 3.1.3 Stopping Rule

As the stopping rule of maximum generation or the minimum criterion of  $F$  value in Equation (1) is satisfied, the evolution process stops, and the solution with the highest fitness value is regarded as the best control vector.

### 3.2 Replacement of individuals by their repaired versions

The question of replacing repaired individuals is related to so-called Lamarckian evolution, which assumes that

an individual improves during its lifetime and that the resulting improvements are coded back into the chromosome. In continuous domains, Michalewicz, Z. and Nazhiyath, G. indicated that an evolutionary computation technique with a repair algorithm provides the best results when 20% of repaired individuals replace their infeasible originals.

#### 4 Application Study

The OPF using Evolutionary Algorithm (EA) has been developed by the use of Borland C++ Builder version 5. More than 6 small-sized test cases were used to demonstrate the performance of the proposed algorithm. Consistently acceptable results were observed. The IEEE 30-bus system with 6 generators is presented here. The total load was 283.4 MW. We propose to apply a genetic algorithm of real type to present active powers of the 6 generators directly. The parameters of the developed EA are: the number of maximal iteration is 5000, the size of population is 70, the crossover used is of heuristic type, the mutation of “non-uniform” type, the operator of selection remains identical as the one of the roulette wheel, the probability of replacement is 0.25 and the power mismatch tolerance is 0.0001 p.u.

Upper and lower active power generating limits and the unit costs of all generators of the IEEE 30-bus test system are presented in Table 1. The NOx emission characteristics of generators are grouped in Table 2.

**Table 1.** Power generation limits and cost coefficients for IEEE 30-bus system.

Bus	$P_{gmin}$ (MW)	$P_{gmax}$ (MW)	$a$ (\$/hr)	$b$ (\$/MW.hr)	$c.10^{-4}$ (\$/MW <sup>2</sup> .hr)
1	50	200	0	2.00	37.5
2	20	80	0	1.75	175.0
5	15	50	0	1.00	625.0
8	10	35	0	3.25	83.0
11	10	30	0	3.00	250.0
13	12	40	0	3.00	250.0

**Table 2.** Pollution coefficients for IEEE 30-bus system

Bus	$a.10^{-2}$	$b.10^{-4}$	$c.10^{-6}$	$d.10^{-4}$	$e.10^{-2}$
1	4.091	-5.554	6.49	2.0	2.857
2	2.543	-6.047	5.638	5.0	3.333
5	4.258	-5.094	4.586	0.01	8.0
8	5.326	-3.55	3.38	20.0	2.0
11	4.258	-5.094	4.586	0.01	8.0
13	6.131	-5.555	5.151	10.00	6.667

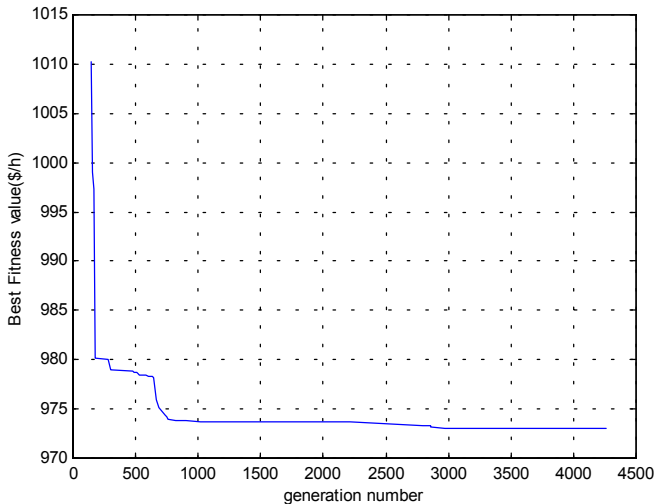
**Table 3.** Results of minimum total cost for IEEE 30-bus system in three cases ( $\alpha=1$ ,  $\alpha=0.5$  and  $\alpha=0$ )

Variable	Initial state	Generation cost minimum	Generation cost + Emission minimum	Emission minimum
$P_{g1}$ (MW)	99.211	180.818	128.2124	66.6384
$P_{g2}$ (MW)	80	48.9381	65.59	65.7536
$P_{g5}$ (MW)	50	18.9533	23.7065	49.9997
$P_{g8}$ (MW)	20	20.5136	26.4992	34.9999
$P_{g11}$ (MW)	20	10.3941	24.6192	29.9395
$P_{g13}$ (MW)	20	13.7138	21.7388	39.9998
Generation cost (\$/hr)	901.9180	803.1060	824.9884	943.1008
Power Loss (MW)	5.8120	9.9308	6.9661	3.9309
Emission (ton/h)	0.2391	0.3771	0.2659	0.2051
Total cost (\$/h)	1033.6	1010.7	971.4	1056.1

The results including the generation cost, the emission level and power losses are shown in Table 3. This table gives the optimum generations for minimum total cost in three cases: minimum generation cost without using into account the emission level as the objective function ( $\alpha=1$ ), an equal influence of generation cost and pollution control in this function and at last a total minimum emission is taken as the objective of main concern ( $\alpha=0$ ). The active powers of the 6 generators as shown in this table are all in their allowable limits. We can observe that the total cost of generation and pollution control is the highest at the minimum emission level ( $\alpha=0$ ) with the lowest real power loss (3.931 MW). As seen by the optimal results shown in the table 3, there is a trade-off between the fuel cost minimum and emission level minimum. The difference in generation cost between these two cases (803.1060 \$/hr compared to 943.1008 \$/hr), in real power loss (9.9308 MW compared to 3.9309 MW) and in emission level (0.3771 Ton/hr compared to 0.2051 Ton/hr) clearly shows this trade-off. To decrease the generation cost, one has to sacrifice some of environmental constraint. The minimum total cost is at  $\alpha=0.5$ . The security constraints are also checked for voltage magnitudes, angles and branch flows. The voltage magnitudes and the angles are between their minimum and the maximum values. No load bus was at the lower limit of the voltage magnitude. The branch MW/MVAR/MVA flows do not exceed their upper and lower limits. These results are not included in this paper.

The figure 1 shows the best fitness found for every generation (for  $\alpha=0.5$ ). We note a fast progress of the value of the best fitness for every generation. The optimum has been obtained after only 1 second for the 5000 generations tested with P4 1.5,GHz,128MO. Ever since the iteration 2968, it converges already, toward the optimum value of the order of 973.05 \$/h.

This value does not take into account the exact cost of the total real power losses. We proceed then to a power flow calculation of type Newton-Raphson and readjust slack generation that takes in consideration the exact losses of real powers. The convergence of the method of N-R is achieved after 4 iterations and 0.1 sec.



**Figure 1** Better Fitness during the EP processes for IEEE 30-bus system

## 5 Conclusion

This paper has reported the use of evolutionary algorithm to solve optimal power flow problem with coordination of environmental and economy objectives. This method would be very useful for power planner and/or operator treat not only cost but also with environmental objective power system. As a study case, the IEEE 30 Bus system with 6-generating units has been selected. The simulation results show that for medium-scale system a genetic algorithm with real code can give a best result with reduced time. To save an important CPU time, the constraints are to be decomposing into active constraints and passives ones. The active constraints are the parameters which enter directly in the cost function and the passives constraints are affecting the cost function indirectly. In this approach, only the active constraints are taken to calculate the optimal solution set using evolutionary programming based on GENECOP III system and the passive constraints are taken in an efficient load flow by recalculating active power of the slack bus. The proposed method can be useful for large scale power system.

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