# Genetic Algorithm Based Optimal Power Flow Solution for Determination of Spot Pricing of Generators in Deregulated Electricity Environment of a Developing Country

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***Abstract*** *– With deregulation and open access of the electricity supply industry occurring internationally, there is an increasing need to develop power market oriented optimal power flow (OPF) algorithm for power systems of developing countries. A genetic algorithm based OPF is proposed for this purpose, which inherits both the real and reactive power constraints with loss expressions involving B-coefficients for active power and C-coefficients for reactive power. The significance of the paper is the development of a flexible OPF methodology using both real and reactive power constraints, which can address a very important issue like determination of the spot price for each participant generator in the economic operation of restructured power systems in the developing countries. The proposed methodology has been tested in a 203 buses 267 lines 23 machines real power system of eastern part of India and the simulation results have established that the proposed method is promising for large scale optimizations under deregulated environments.*

**Keywords**: Electricity deregulation; optimal power flow; genetic algorithm; spot price.

## 1. INTRODUCTION

In the past few years the interest in OPF has become more pronounced. Many optimization techniques have been adopted and used to solve the OPF problem viz. fuzzy emissions constraints[1],particle swarm optimization[2],[3],[4] distributed OPF method[5], clonal algorithm[6], interior point method[7], semi-finite programming[8], extended conic quadratic Formulation[9], evolutionary algorithm [10], iterative approach[11], quantum inspired evolutionary algorithm[12] and computational intelligence techniques[13]. In other associated papers [14], [15], [16], [17] and [18], genetic algorithm has also been used to solve OPF problem with the active power optimization only.

The electric power industry in India is in transition to a deregulated market place for power transactions. In this environment, all power transactions are based on price rather than cost. In this price based competition, an unambiguous, transparent, and predictable pricing framework of electricity is one of the major issues in the economics of the power system operation. Therefore, with this growing interest in determining the costs of supplying the ancillary services needed to maintain quality and reliable electricity service, the spot price should be calculated in a scientific way. Literature survey reveals that the concept of spot price was introduced in to cope up with the different problems of continuous changing electricity rate structure and the DC load flow method has been employed initially to determine the spot price [19]. In subsequent literatures spot price model has been simulated using decoupled OPF [20], successive quadratic programming [21], Newton OPF interior point method [22] and Benders partition algorithm [23]. These published literatures mostly discussed the related work using 6-bus, 9-bus, and conventional IEEE test systems.

In this paper the spot pricing model has been employed and the optimal power flow has been solved as a constrained nonlinear optimization problem using genetic algorithm with fitness scaling that permits the efficient and effective handling of large sets of equality (power flow) and inequality constraints within the problem solution. A detail case study has been performed in a real power system in eastern grid of India to solve the OPF problem with both active and reactive power constraints. In this region the generator is predominantly thermal and the power network has 203 buses, 267 lines and 23 thermal generators. The results indicate the variation of spot prices for each generator in the deregulated electricity market.

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## 2. NOMENCLATURE

In the analytical model following symbols have been used:

$F_{c_{total}}$ : Cost function of an N-bus power systems having NG number of fossil fuel units

N : Number of buses

$\alpha, \beta, \gamma$ : Cost coefficients of the thermal generators

$B_{ij}$ and $C_{ij}$: Loss coefficients for active and reactive power respectively

$\phi$ : Power factor angles of bus load

$\delta$ : Phase angles of bus voltages

$P_D$ and $Q_D$ : Real and reactive power demands

$P_g$ and $Q_g$ : Real and reactive power outputs

$P_L$ and $Q_L$ : Real and reactive loss in the transmission system .

$R_{ij}$ and $X_{ij}$ : Series resistance and reactance of transmission lines.

$\lambda_{p_i}$ and $\lambda_{q_i}$ : Lagrangian multiplier for active power and reactive power balance at the i[th] bus respectively

[H] : Hessian Matrix

[J] : Jacobian Matrix

$g(x,u)=0$ : Equality constraint

$h(x,u)\le 0$ : Inequality constraint

ε : Tolerance limit

$\rho_{p_i}$ : Spot price of i[th] generator

$\sigma$ : Profitability coefficient

Suffix i stands for i[th] bus while suffix j stands for j[th] bus. The variables have been expressed in p.u. while the angles have been expressed in degree.

## 3. PROBLEM FORMULATION USING GENETIC ALGORITHM

Genetic algorithm (GA) [24] is a global adaptive search technique based on the mechanics of natural genetics. GA uses a direct analogy of natural behavior. It is applied to optimize existing solutions by using methods based on biological evolution such as the ones presented by Charles Darwin. It has many applications in certain types of problems that yield better results than the commonly used methods. To solve a specific problem with GA, a function known as fitness function needs to be constructed which allows different possible solutions to be evaluated. The algorithm will then take those solutions and evaluate each one, deleting the ones that show no promise towards a result but keeping those which seem to show some activity towards a working solution.

One of the advantages of genetic algorithm is that it is a parallel process because it has multiple offspring thus making it ideal for large problems where evaluation of all possible solutions in serial would be too time taking, if not impossible. The main critical point of genetic algorithm is selection of the initial population otherwise the convergence procedure may show the unsatisfied answer.

The main advantage of fitness scaling introduced in this paper is the range of the scaled values affecting the performance of the genetic algorithm. If the scaled values vary widely, the individuals with the highest scaled values reproduce rapidly, taking over the population gene pool too quickly, and preventing the genetic algorithm from searching other areas of the solution space. On the other hand, if the scaled values vary only a little, all individuals have approximately the same chance of reproduction and the search will progress slowly.

### 3.1. Problem formulation considering power flow requirements within GA

The OPF is a constrained optimization problem requiring minimization of an objective function. The objective function being the total cost of power generation, we have

$$\min GC(x,u) \text{ i.e. } \sum_{i=1}^{NG} F_c(P_{G_i}) \tag{1}$$

subject to

$$g(x,u)=0 \tag{2}$$

$$h(x,u)\le 0 \tag{3}$$

The equality constraints (2) are the power flow equations, while the inequality constraints (3) are due to various operational limitations. The limitations include lower and upper limits of generator real and reactive power capacity, limits on voltage magnitudes and settings of possible transformer tap positions.

#### *3.1.1. Problem encoding*

Each control variable is called a gene, while all control variables integrated into one vector is called a chromosome. The GA always deals with a set of chromosomes called a population. Transforming chromosomes from a population, a new population is obtained, i.e., next generation is formed. It needs three genetic operators: selection, crossover, and mutation for this purpose.

#### *3.1.2. Initialization:*

Usually, at the beginning of the GA optimization process, each variable gets a random value from its predefined domain. The generator power outputs have well-defined lower and upper limits, and the initialization procedure commences with these limits given by

$$P_{g_i}^{\min} \le P_{g_i} \le P_{g_i}^{\max} \quad \text{and} \quad Q_{g_i}^{\min} \le Q_{g_i} \le Q_{g_i}^{\max}.$$

#### *3.1.3. The fitness functions and parent selection*

Implementation of a problem in a genetic algorithm is realized within the fitness function. Since the proposed approach uses the equal incremental cost criterion as its basis, the constraint equation can be rewritten as

$$\varepsilon = \sum_{i=1}^{n} P_{g_i} - P_D - P_L \qquad (4)$$

while the penalty factor, being selected as the fitness function, is given by [25]

$$\frac{dF_c(P_{g_i})}{dP_{g_i}}\left[\frac{1}{1-\dfrac{\partial P_L}{\partial P_{g_i}}}\right] = \lambda \qquad (5)$$

Convergence is obtained when ε is less than tolerance.

Improvement of the average fitness of the population is achieved through selection of individuals as parents from the completed population. The selection is performed in such a way so that chromosomes having higher fitness are more likely to be selected as parents.

Rank fitness scaling is used in this paper converts the raw fitness scores which are returned by the fitness function to values in a range that is suitable for the selection function. It also removes the effect of the spread of the raw scores. The selection function uses the scaled fitness values to select the parents of the next generation. It assigns a higher probability of selection to individuals with higher scaled values.The scaled fitness value of an individual with rank *n* is proportional to $1/\sqrt{n}$ .

### *3.1.4. Crossover and Mutation*

After the selection, the GA applies a random generator to cut the strings at any position (the crossover point) and exchanges the substrings between the two chromosomes. Once the crossover is performed, the new chromosomes are added to the new population set. Mutation being another parameter, it involves randomly selecting genes within the chromosomes and assigning them random values within the corresponding predefined interval. The probability of mutation is normally kept very low, as high mutation rates could degrade the evolving process into a random search process.

### *3.1.5. Parameter selection:*

Like other stochastic methods, the GA has a number of parameters that must be selected. These include: size of population, reproduction, probability of crossover, and probability of mutation. The population size should be large enough to create sufficient diversity covering the possible solution space. In this paper, GA has been employed with fixed number of generations while other parameters, such as crossover probability, mutation rate, and selection seem to affect the GA process less significantly when evaluated over a large number of generations.

The flowchart of the proposed optimization procedure is shown in Fig.1.

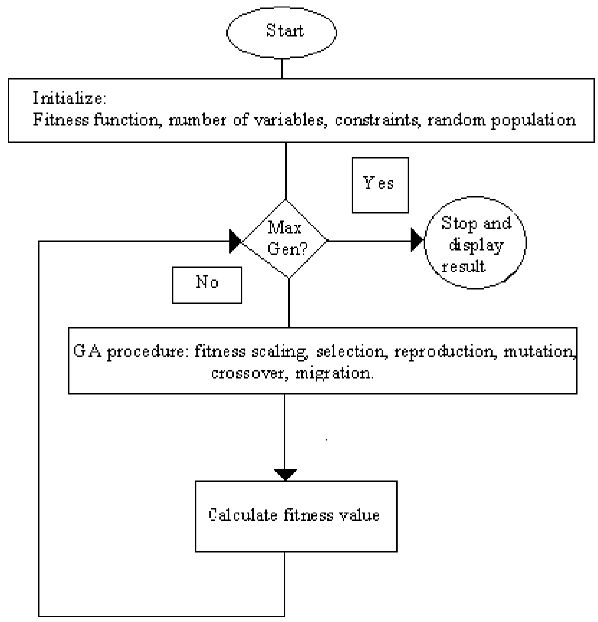



**Fig. 1.** Flowchart of the proposed optimization procedure.

## 4. SPOT PRICE MODELING UNDER OPF CONDITION

The spot price of participating generator has been calculated in this paper from genetic algorithm based optimal power flow. When spot pricing is a major concern for electricity, it seems natural to generate prices on a time scale determined by the contract. In this paper, generation of hourly prices has been derived instead of daily averages using optimal generating cost based on stochastic demand and supply.

The generation cost of the i$^{th}$ generator is conventionally represented as

$$F_{c_{total}}\left(=\sum_{i=1}^{NG} F_{c_i}\right) = \sum_{i=1}^{NG} \alpha_i \left(P_{g_i}\right)^2 + \beta_i P_{g_i} + \gamma_i$$

$/hr with a linear incremental cost function, where $\alpha, \beta$ and $\gamma$ are the cost coefficients and $P$ is the real power generation of the i$^{th}$ generator. The spot price inherits the objective function from classic economic dispatching with the extension to include loss compensation cost. The spot price of each participant generator at optimal condition can thus be obtained as

$$\rho_{P_{g_i}} = \sigma \int_{P_{g_i}} \frac{1}{1-\dfrac{\partial p_L}{\partial p_{g_i}}} \frac{\partial FC_i}{\partial P_{g_i}} \text{ \$/MWhr} \qquad (6)$$

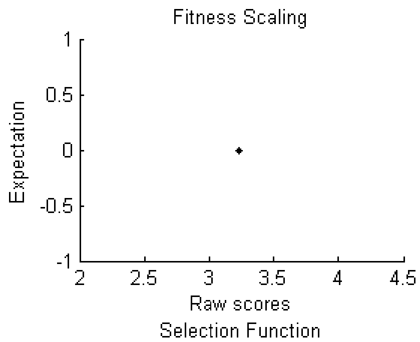
Equation (15) indicates the spot price of active power which is composed of marginal generating cost, loss component as well as profitability coefficient. In this paper the cost of reactive power generation has not been accounted for as it is apparent that the price of reactive power would be null when the generation capacity constraints are not violated [22].

## 5. SIMULATION

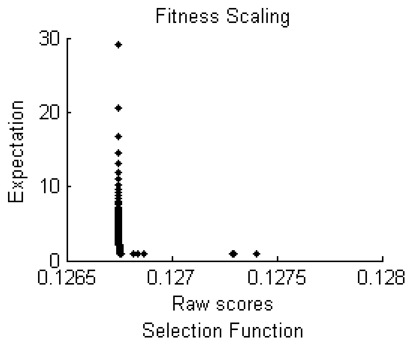
To examine the validity of GA model for optimizing the power generation of the participating generators as well as spot price calculation in the deregulated electricity market, a real 203 buses 23 machines 267 lines power system of eastern grid of India has been considered. The optimization technique includes both real and reactive power constraints as well as appropriate scaling of the fitness function. The network loading condition of 75.94 p.u. active and 47.9253 p.u. reactive power is used to perform OPF and calculate spot prices.

### 5.1. GA programming flow

In this section the objective function of OPF is evaluated using genetic algorithm. The programming flow is demonstrated using successive graphical plots (Figure: 2(a&b), 3(a&b), 4(a&b)). In these figures, selection functions, variation of fitness values with respect to generations, stall generation and stall time limit (stopping criterion of GA) are portrayed.

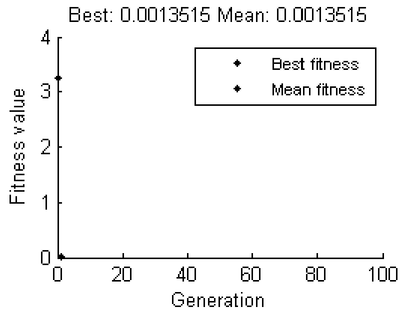


**(a)**



**(b)**

**Fig. 2 (a)** and **(b).** Expected number of children versus the raw scores at each generation for active power and reactive power respectively.



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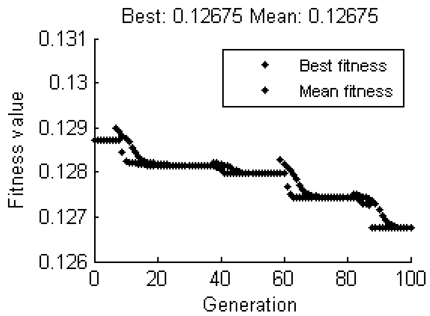
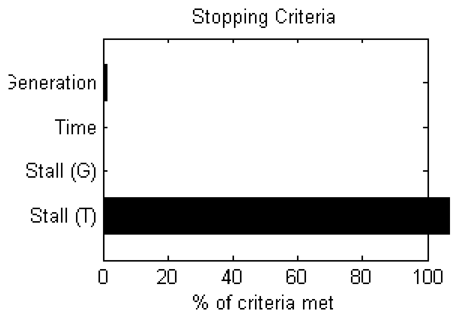


**(b)**

**Fig. 3 (a)** and **(b)**. Best fitness function value versus generation for active and reactive power respectively.



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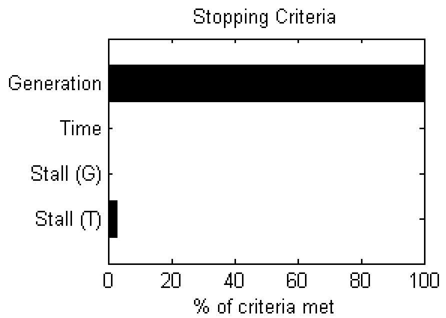


**(b)**

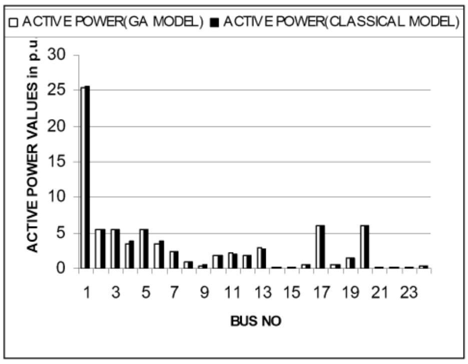
**Fig. 4 (a)** and **(b)**. Stopping criteria levels for active and reactive power respectively.

### 5.2. Final results

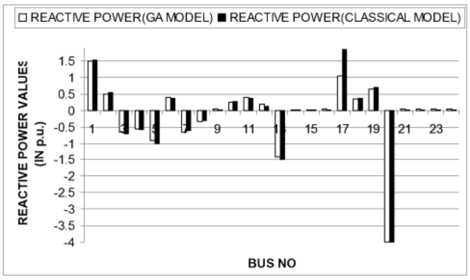
Figure 5(a) and 5(b) reveal the final OPF results of active and reactive power of all generator buses (including bus no 1, the slack bus) under given loading condition. The bar chart shows the comparative results of optimal power outputs with the classical method (briefly explained in the Appendix) and GA (with fitness scaling). It has been shown that the GA result is comparatively same as classical OPF result.

### 5.3. Spot price calculation

The profile of spot price for each of the generator buses of the respective system has been furnished in figure 6 also with classical method based spot pricing profile. It reveals that under the given loading condition, spot price for active power is dominated by system lambda and network loss components.




**(a)**




**(b)**

**Fig. 5 (a)** and **(b).** Bar charts comparing the results available for optimum values of real and reactive power generation of the generators using classical method and GA model.

It has been shown that OPF solution is essential for OPF based pricing schemes. Figure 6 depicts that spot pricing obtained using GA and classical method is almost same. The GA based OPF is in advantageous position for its simplicity as well as less time consuming which is most desirable for ISO in deregulated system.

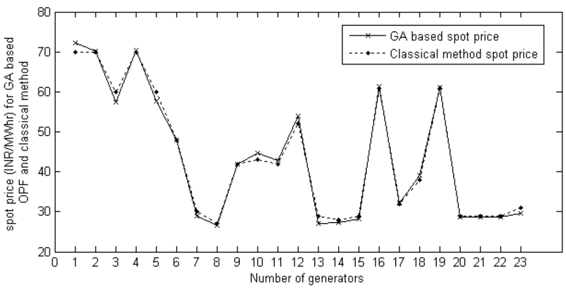



**Fig. 6.** Variation of spot prices of different generators for GAOPF and classical method.

### 5.4. Computation time

The computational time for the whole OPF run for the practical system using the classical method (furnished in the Appendix) and GA (with fitness scaling) has been recorded in Table. 1. It has been observed that the CPU time taken by GA is lesser than that by the classical method.

**Table 1:** Computation time using classical method and GA.

| OPF solve | Classical method | With genetic algorithm |
|---|---|---|
| CPU time(sec) | 52.59 | 23.219 |

## 6. CONCLUSION

Deregulation in the electric power industry in India is expected to increase the benefits associated with the operation of interconnected power systems. In this paper, we have employed the GA model with fitness scaling to solve the real and reactive power constrained optimal power flow problem for a real 203 buses 267 lines 23 machines power system in order to evaluate the spot price of participants in a deregulated energy market. The model has been implemented by modifying classical OPF methods through genetic algorithm, which can effectively simplify the calculation of spot price as well as maintain the power balance equation. The validity of the GA model has also been justified comparing the proposed model with the conventional iterative method of OPF solution. It has been observed that the problem formulation becomes simpler in the GA model with fitness scaling and the CPU time for execution of the program is much lesser compared to the conventional method.

The analysis is useful to the Pool coordinators to identify spot prices at optimal situations and to encourage pricing policies that lead to maximum system-wide benefits. Participants in deregulated power pools can also use the specific aspects of the proposed analysis for price definition and decision making processes.

## REFERENCES

1. Ramesh V.C., LIX., Optimal power flow with fuzzy emissions constraints, Taylor & Francis publication, International journal of electrical machines and power systems 25(1997) 897-906.
2. Abido, M.A., Optimal power flow using particle swarm optimization, Elsevier Sci Ltd, International journal of electrical power, energy systems 24(5)(2002) 563-571.
3. Lingfeng wang, Chanan Singh, Environmental/economic power dispatch using a fuzzified multi-objective particle swarm optimization algorithm, Elsevier Inc, Electric power systems research 77(12)(2007) 1654-1664.
4. M.A. Abido, Multiobjective particle swarm optimization for environmental/economic dispatch problem, Elsevier Inc, Electric power systems research 79(7)(2009) 1105-1113.
5. Hur D. and Kim B., Application of distributed optimal power flow to power system security assessment, Taylor & Francis Ltd, International journal of electric power components and systems 31(1)(2003) 71-80.
6. B.K. Panigrahi, Salik R. Yadav, Shubham Agarwal, M.K. Tiwari, A clonal algorithm to solve economic load dispatch, Elsevier Inc, Electric power systems research 77(10) 1381-1389.
7. Wei Yan, Juan Yu, David C. Yu, Kalu Bhattarai, A new optimal reactive power flow model in rectangular form and its solution by predictor corrector primal dual interior point method, IEEE transactions on power systems 21(1)(2006) 61-67.
8. Yan Xia, Ka Wing Chan, Dynamic constrained optimal power flow using semi-infinite programming, IEEE transactions on power systems 21(3)(2006) 1455-1457.

9. Rabih A.Jabr, Optimal power flow using an extended conic quadratic formulation, IEEE transactions on power systems 23(3)(2008) 1000-1008.
10. M.M.EI Metwally, A.A.EI Emary, F.M.EI Bendary, M.I. Mosaad, Optimal power flow using evolutionary programming techniques, IEEE transactions on power systems (2008) 260-264.
11. Florin Capitanescu, Louis Wehenkel, A new iterative approach to the corrective security constrained optimal power flow problem, IEEE transactions on power systems 23(4)(2008) 1533-1541.
12. John G. VIachogiannis, Kwang Y. Lee, Quantum inspired evolutionary algorithm for real and reactive power dispatch, IEEE transactions on power systems 23(4)(2008)1627-1636.
13. M.R. Al Rashidi, M.E.EI-Hawary, Applications of computational intelligence techniques for solving the revived optimal power flow problem, Elsevier Inc, Electric power systems research 79(4)(2009) 694-702.
14. L.L. Lai, J.T. Ma, R. Yokoyama, M. Zhao, Improved genetic algorithms for optimal power flow under both normal and contingent operation states, Elsevier Sci Ltd, International journal of electrical power, energy systems 19(5)(1997) 287-292.
15. Angela S. Chuang, Felix Wu, An extensible genetic algorithm framework for problem solving in a common environment, IEEE transactions on power systems 159(2000) 269-275.
16. M.S. Osman, M.A. Abo-Sinna, A.A. Mousa, A solution to the optimal power flow using genetic algorithm, Elsevier Inc., International journal of applied mathematics and computation 155(2)(2004) 391-405.
17. Mirko Todorovski, Dragoslav Rajičić, An initialization procedure in solving optimal power flow by genetic algorithm, IEEE transactions on power systems 21(2)(2006) 480-487.
18. Wei Yan, Fang Liu, C.Y. Chung, K.P. Wong, A hybrid genetic algorithm-interior point method for optimal reactive power flow, IEEE transactions on power systems 21(3)(2006)1163-1169.
19. F.C. Schweppe, M.C. Caramanis, R.D. Tabors, R.E. Bohn, Spot Pricing of Electricity, MA Kluwer academic publishers (1988).
20. A.A. El-Keib, X. Ma, Calculating of short-run marginal costs of active and reactive power production, IEEE trans. on power system,12 (1)(1997) 559-565.
21. J.D. Finney, H.A. Othman, W.L. Rutz, Evaluating transmission congestion constraints in system planning, IEEE trans. on power systems, 12 (3) (1997).
22. Kai Xie, Yong-Hua Song, John Stonham, Erkeng Yu, Guangyi Liu, Decomposition model and interior point methods for optimal spot pricing of electricity in deregulation environments, IEEE trans. on power systems, 15 (1) (2000) 39-50.
23. Ying-Yi Hong, Ming-Ting Weng, Optimal short-term real power scheduling in a deregulated competitive market , Elsevier Inc, Electric power systems research, 54 (3) (2000) 181-188.
24. David E. Goldberg, Genetic algorithms in search, optimization & machine learning, third impression, Pearson education Inc, 2008.
25. Abhijit Chakrabarti, Sunita halder, Power system analysis, operation and control, third ed., PHI learning Pvt. Ltd, India, 2010.



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