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Genetic Algorithm based Generation Cost Constrained Re-dispatching Schedule in Deregulated Power Market

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Abstract

Optimal pricing of electricity in a power system was proposed during early eighties considering unit generation and consumer usages as decision variables. With restructuring followed by deregulation, a number of players have started participating in the competitive power market leading optimal pricing of electricity to a complicated level. Literature survey reveals that different models have been proposed and solved for evaluation of optimal prices using classical methods but many issues have not yet been exposed. This paper presents a novel algorithm for optimal allocation of generation schedule of generators to optimize generation cost under stressed condition of a system considering consumer welfare. Here, the optimal generation dispatch problem is formulated as a non-linear constrained optimization problem where real power generation and total generation cost are to be optimized simultaneously. This proposed algorithm has been tested with standard IEEE 30 bus system using genetic algorithm. The results demonstrate the capabilities of the proposed approach to generate true and well distributed optimal solution of the dispatch problem in one run even in stressed condition of the system.

Index Terms: Deregulated power market, Genetic Algorithm, Generation cost, Re-dispatching schedule

Introduction

In recent years, the electricity industry has been under-going unprecedented restructuring all over the world. Regulated or state-owned monopoly markets have been deregulated [1]. This process is intended to open the power sector to market forces with the ultimate target of reducing consumer prices that bring about consumer welfare. Therefore, central ideology of electric power industry deregulation is that the delivery of power must be decoupled from purchase of the power itself, and be priced and contracted separately [2]. One of the major issues of this price-based competition is transparency and predictable pricing framework. With this growing interest in determining the cost of power and ancillary services, many real time pricing methods were established.

For a participant in deregulated power market, two things need to be fully examined e.g. (i) the relationship between competitive requirements and market structures (ii) optimal operation of supply and demand in terms of consumer welfare. Decisions regarding the operation of power plants are based on forecasted electricity prices. From economic point of view, active power pricing in competitive power market in variable loading conditions presents a good potential for providing valuable instructions for system operations. 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 [3], particle swarm optimization [4] distributed OPF method [5], interior point method [6], extended conic quadratic formulation [7], evolutionary algorithm [8], iterative approach [9], quantum inspired evolutionary algorithm [10] and computational intelligence techniques [11]. Different models of earlier researches provide a background and motivation for the development of an integrated soft computing model for optimal allocation of generated power with minimal generation cost under stressed conditions of loading without any complicated classical computation. The proposed generation cost constrained power rescheduling model is solved as a constrained non-linear optimization problem using genetic algorithm that permits competent and effective handling of a large set of equality and inequality constraints within the problem solution.

In a deregulated electricity market, it is quite indispensable to optimize the instantaneous price of electricity as well as generated power at a particular state of demand from both generation and distribution point of view and, genetic algorithm is a stochastic method that is applied to the model of biological processes to solve the optimization problem with an advantage of dealing with the integer variables. GA does not require any prior knowledge, space limitations, or special properties of the function to be optimized, such as smoothness, convexity or existence of derivatives. It can be applied using binary and continuous approaches. Another advantage 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. In other review papers [12], [13] and [14] genetic algorithm has also been used to solve optimal power flow problem, however, the generation cost optimization is not incorporated as objective function of GA in those papers.

This paper focuses on the issues related to active power pricing in competitive power market under variable load conditions. Early attempts of this approach either concentrated on optimizing price at fixed demand or optimizing power flow using genetic algorithm in regulated power environment. But those models could not create a transparent competition between Gencos in different stressed conditions in deregulated environment. The proposed genetic algorithm is utilized for getting re-dispatching schedule of generated powers in real time operations to optimize the price of electricity by optimizing generation cost for consumer welfare i.e. the consumer price will be as close as possible to cost of electricity. The proposed model has been successfully tested with IEEE 30 bus standard test system using genetic algorithm, which produce satisfactory results avoiding any classical calculation of generation cost.

Theory

Electricity pools are market institutions designed to permit trade and competition in the supply of energy whilst simultaneously allowing the overall control and co-ordination of generation and transmission. In deregulated environment, Independent System Operator (ISO) regulates the market. The one of the main tasks of ISO is to lead the pool market to a short run economic optimum. In order to achieve this aim, market operator collects electrical power bids from supplier as well as consumers in a certain time interval and after analyzing the power situation, they develop strategies to define transactions among participants by searching for the minimum price that satisfies the power demand in order to maximize social welfare. The generation cost of the i^{th} generator is represented as $C(i)=\alpha(i)P(i)^2+\beta(i)P(i)+\gamma(i)$ with a linear incremental cost function, where α, β and γ are the cost coefficients and P is the real power generation by the i^{th} generator.

Typical bid curves [15] for the supplier and consumer are illustrated in Fig. 1. The supply and demand bid curves determine the optimum price to sell and buy a certain quantity of electrical power considering both consumer welfare and competency of suppliers.

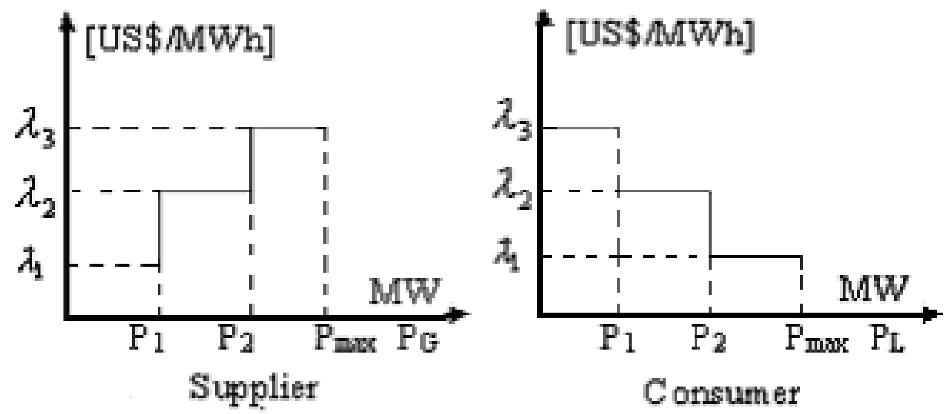

Figure 1: Supplier and consumer bid curves.

The objective function of the OPF can be considered as to maximize the social welfare by minimizing the global system costs and thereby maximizing the profit of all market participants. The objective function is given in (1) considering, for the simplicity, one step bid curves are applied for suppliers and consumers:

$$C_1\left(P_G, P_{UL}\right) = \lambda_{MIN}^T P_G + \lambda_{MAX}^T P_{UL} \quad (1)$$

where, C_1 - the total generation costs , P_G - generation power, P_{UL} - uncovered load, λ_{MIN} - minimal acceptable price of the suppliers, λ_{MAX} - maximal acceptable price of the consumers

The uncovered load, a part of a particular load that cannot be covered if the load bid for the part is lower than the suppliers' bid or if system has congestions, can be modeled as a fictitious generator and from the consumer bid curve (Fig. 1), the bid curve of fictitious generator has been developed [15], as shown in Fig. 2. A part of fictitious generator is dispatched if the corresponding bid price is lower than the suppliers' bid. This generator can also be dispatched if system congestions prevent the full cover of the load. For a load located at bus i

$$0 \le P_{ULi} \le P_{MAXi} \text{ and } P_{L_i} = P_{LMAX_i} - P_{UL_i}$$

where, P_{Li} – covered load portion at bus *i*, P_{LMAXi} - maximum load demand at bus i,

Therefore, the above-mentioned OPF objective function in the pool market can be now formulated as:

$$C_1\left(P_G\right) = \lambda_{MIN}^T P_G \quad (2)$$

where P_G represents the conventional generators and fictitious generators.

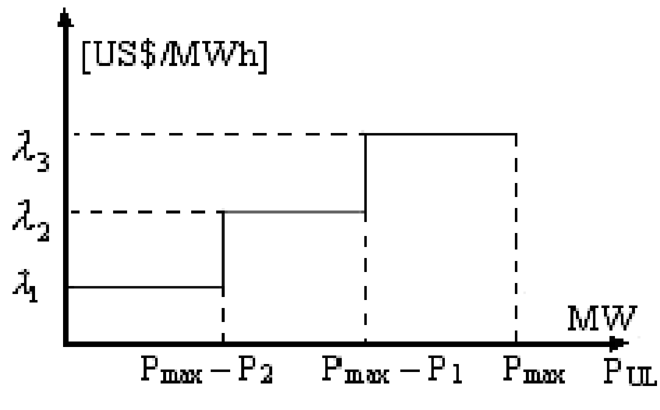

Figure 2: Bid curve of fictitious consumer generator.

Problem formulation using GA

The formulation of the optimal value of generation cost and generated power can be expressed as follows:

$$\min C_{TOTAL} = C_1(P_G) \tag{3}$$

subject to conventional equality constraints and inequality constraints of optimal power flow, where from (2), $C_1(P_G) = \lambda_{\min}^T P_G$

$C_1(P_G)$, the total generation cost is defined as

$$C_{total}\left(=\sum_{i=1}^{NG} C_i\right) = \sum_{i=1}^{NG} \alpha_i \left(P_{G_i}\right)^2 + \beta_i P_{G_i} + \gamma_i \tag{4}$$

P_G - Power generation of generators

The equality constraints are the power flow equations, while the inequality constraints are due to various operational limitations. The limitations include lower and upper limits of generator real power capacity; power demand of the system etc.

Problem Encoding

Each control variable is called a gene, while all control variables integrated into one vector is called a chromosome. If the chromosome has N_P parameters (an N dimensional optimization problem) given by p_1, p_2……p_{Np}, then the single chromosome is written as an array with 1 * N_P elements as follows:

$$\text{Chromosome}=\left[p_1, p_{2.........} p_{Np}\right] \tag{5}$$

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.

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

$$P_{G_i}^{\min} \le P_{G_i} \le P_{G_i}^{\max} \text{ And } P_D \le P_G \tag{6}$$

Fitness function and parent selection

After encoding, the objective function (fitness) will be evaluated for each individual of the population. In this work, the fitness is defined as follows:

$$\text{Fitness}= (\text{S-}\, C_{TOTAL}) \tag{7}$$

Here S is the predefined range of generation cost and C_{TOTAL} has been considered as total cost price of generated power. In this paper, the limit of S has been assumed within 2000 to 2500 US$/hr considering practical tariff structure.

Constraints function is achieved using the conventional power balance relation given as follows:

$$\varepsilon = \sum_{i=1}^{n} P_{G_i} - P_D - P_L \tag{8}$$

P_L, the loss term is expressed using B-coefficient [16] as follows:

$$P_L = \sum_{i=1}^{n}\sum_{j=1}^{m} P_{Gi} B_{ij} P_{Gj} = B_{00} + \sum_{i=1}^{n} B_{i0} P_{Gi} + \sum_{i=1}^{n}\sum_{j=1}^{m} P_{Gi} B_{ij} P_{Gj} \tag{9}$$

where $$B_{ij} = \frac{\cos(\theta_i - \theta_j) R_{ij}}{\cos\varphi_i \cos\varphi_j \, |V_i||V_j|} \text{ and } B_{i0} = -\sum_{j=1}^{m} (B_{ij} + B_{ji}) P_{Dj} \tag{10}$$

Crossover and Mutation

Crossover is an extremely important operator for GA. It is responsible for the structure recombination (information exchange between mating chromosomes) and the convergence speed of GA and is usually applied with high probability (0.6–0.9). The chromosomes of the two parents selected are combined to form new chromosomes that inherit segments of information stored in parent chromosomes. Mutation is used to introduce some sort of artificial diversification in the population to avoid premature convergence to local optimum. The probability of mutation is normally kept very low, as high mutation rates could degrade the evolving process into a random search process.

Parameter selection

Resembling other stochastic methods, GA has a number of parameters to 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 with fixed number of generations and other parameters are used, such as crossover probability, mutation rate, and selection seem to affect the GA process less significantly when evaluated over a large number of generations. In this model, GA parameters are set as follows: Population size: 20 (For 6 numbers of generators), Mutation: Adaptive feasible, Migration: Forward, Elite counts: 5, Fitness limit: Zero.

The Independent System Operator, in the proposed model, can be guided according to the flow chart as shown in Fig. 3 to choose the re-dispatching schedules of generators to get optimum generation cost for consumer welfare.

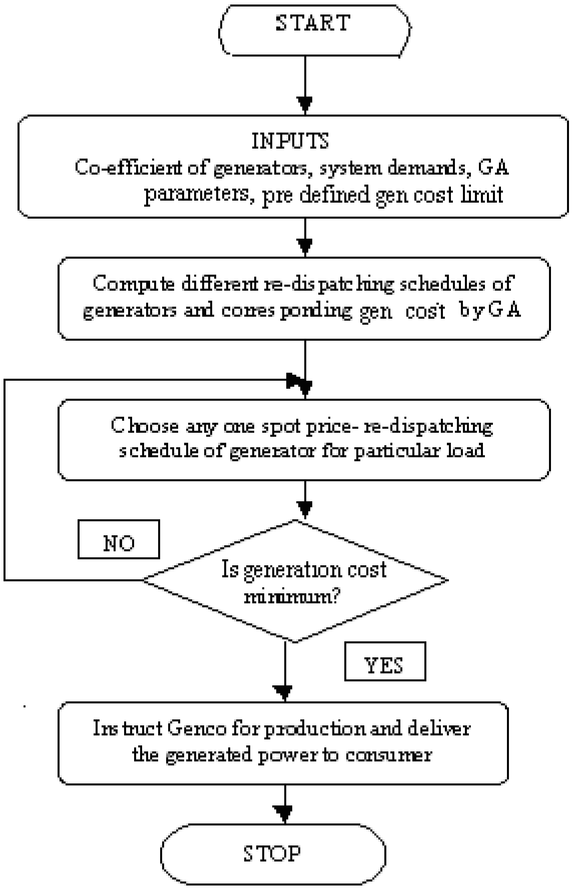

Figure 3: Flowchart of proposed re-dispatching generation schedule for different loading condition.

Simulation and Results

Electricity prices in a restructured power system may be highly volatile due to system demand. It is, therefore, very difficult for ISO to control the price of electricity without any definite statute. With the help of the proposed algorithm, ISO can reconcile electricity price for both buyer and seller of electricity. Here to examine the validity of GA model as described by (7) for optimizing the generation cost as well as power generation of the generators, IEEE 30 bus test system has been considered. The test system and production units' properties are given in Tables I and II.

Table I: Configuration of the Test System.

Number of buses	30
Number of generator units	6
Number of branches	43
Number of tie lines	6

Table II: Production Unit Details.

Generator No	P_{max} (MW)	P_{min} (MW)	Cost Co-efficient		
			α_i	β_i	γ_i
1	145.5	120.5	0.074	1.083	25
2	70.6	50.6	0.089	1.033	24
3	35.6	20.4	0.089	1.033	22
4	50	30	0.074	1.083	21
5	25.9	10.8	0.089	1.033	23
6	25.9	10.8	0.053	1.17	29

The proposed methodology has been studied considering the following three cases.

Case I: Optimal generation at minimum generation cost for a fixed demand

Optimized values of generated power for all generators including total generation cost have been determined by GA considering all equality and inequality constraints of optimal power flow as mentioned in (6) and (8). Table III illustrates the solution obtained by GA for total generation cost and optimum percentage loading of each generator with respect to their maximum capacity as well as generated powers in MW maintaining the generation cost near minimum value for a fixed demand.

Table III: Optimal Dispatch Schedule of Generators and Total Generation Cost for Fixed Demand.

Gen 1	Gen 2	Gen 3	Gen 4	Gen 5	Gen 6	Generation cost US$/hr
Percentage Loading of generator w. r. to P_{max} (Generation in MW)						
82.82 (120.5)	71.67 (50.6)	88.17 (31.4)	89.08 (44.54)	83.7 (21.6)	83.7 (21.69)	2058.9

Case II: Contribution of individual Genco under variable loading conditions at optimum generation cost

The total demand has been increased up to 10% with a step of 2% and accordingly generated power and total generation cost has been optimized using genetic algorithm. Table IV demonstrates the rescheduled generations of individual generator for incremental demand and corresponding optimized generation cost. From this model the ISO will be able to advice a Genco to reschedule the generators for optimum generation cost under stressed condition of loading. It can also be inferred from Table IV that the generators of higher ratings cater less stress than the generators of lower rating. This rescheduling technique emphasizes efficient load distribution while optimizing generation cost.

Table IV: Optimal Redispatching Schedule Of Gencos And Total Generation Cost For Incremented Demand .

System Demand	Rescheduled Generation						Generation cost US$/hr
	Gen 1 MW	Gen 2 MW	Gen 3 MW	Gen 4 MW	Gen 5 MW	Gen 6 MW	
Base case	120.5	50.6	31.4	44.54	21.6	21.69	2058.9
2 % increase	120.5	50.6	32.6	47	22.9	22.89	2095.9
4 % increase	120.5	50.6	34.2	48.57	24.5	24.47	2133.9
6 % increase	120.5	52.4	35.3	49.59	25.5	25.49	2178.3
8 % increase	121.7	54.5	35.6	49.99	25.9	25.89	2233.2
10 % increase	125.3	60.6	35.5	49.99	25.9	25.89	2371.7

For optimal re-dispatching schedule of each generator with incremented demand (obtained from Table IV), cost price of individual generator has been calculated and shown in Table V. This analysis helps individual Genco to ascertain its own economic status in the market with respect to the minimum generation cost.

Table V: Variation of Cost Price of Generated Power with Incremented Demand.

Demand	Gen 1 US$/hr	Gen 2 US$/hr	Gen 3 US$/hr	Gen 4 US$/hr	Gen 5 US$/hr	Gen 6 US$/hr
BASE CASE	1230	304.14	142.18	216.06	87.32	79.33
2 % increase	1230	304.14	150.26	235.37	88.32	83.57
4 % increase	1230	304.14	161.25	248.22	101.59	89.32
6 % increase	1230	322.69	168.6	256.74	107.19	93.29
8 % increase	1253.8	344.08	171.58	260.15	109.46	94.95
10 % increase	1322.6	413.29	171.59	260.15	109.47	94.86

Case III: Breakeven operation in deregulated system

The allocation of loading to generators with the increment of demand should be cost effective for both Genco and consumer point of view. The previous researches concentrated on a fixed allocation of load according to generation cost. But several other re-dispatching schedules of generators are possible for optimum generation cost. Tables VI and VII show different re-dispatching schedules of generators, keeping one of the generators fixed at its generation prior to increase in demand and corresponding total generation cost within predefined limit for increased load value. Combinations B to G of Table VI and Table VII describe the different re-dispatching schedules where a particular generator did not take part to deliver additional power during stressed condition i.e in combination B the generation of Generator 1 and that of Generator 2 in combination C, are kept fixed at its generation prior to increase in demand and so on. Figures 4 and 5 show the variation of optimum generation cost with different combinations of loading. These two figures depict that ISO has different options of allocating load to generators to maintain generation cost at its minimum possible value for 10% and 6% increment in demand respectively. From these re-dispatching schedules, ISO can choose one where the generation cost is optimum. For instance, for 10% increment in demand, re-dispatching schedule B (Fig. 4) is the most appropriate one from the buyer's point of view where as for 6% incremented load schedule C (Fig. 5) is found to be the suitable one.

Table VI: Different Re-Dispatching Schedules of Gencos and Generation Cost for 10% Incremented Demand.

	Gen 1	Gen 2	Gen 3	Gen 4	Gen 5	Gen 6	Generation cost US$/hr	Remarks
	Percentage Loading for 10% increment in demand							
A	86.12	85.83	99.71	99.98	99.96	99.96	2371	No Gen is fixed
B	82.82	92.62	99.99	99.99	99.99	99.99	2337.71	Gen 1 is fixed
C	92.98	71.67	99.99	99.99	99.99	99.99	2465.71	Gen 2 is fixed
D	86.12	91.76	88.17	99.99	99.99	99.99	2393.71	Gen 3 is fixed
E	87.82	89.62	99.99	89.08	99.99	99.99	2410.71	Gen 4 is fixed
F	85.92	92.16	96.26	99.99	83.77	99.99	2383.71	Gen 5 is fixed
G	86.25	91.45	99.99	99.99	99.99	83.77	2408.69	Gen 6 is fixed

Table VII: Different Re-Dispatching Schedules of Gencos and Generation Cost for 6% Incremented Demand.

	Gen 1	Gen 2	Gen 3	Gen 4	Gen 5	Gen 6	Generation cost US$/hr	Remarks
	Percentage Loading for 6% increment in demand							
A	82.81	74.23	98.86	99.98	99.19	99.19	2178.33	No Gen is fixed
B	82.82	74.23	98.86	99.98	99.19	99.19	2178	Gen 1 is fixed
C	82.95	71.67	99.99	99.99	99.99	99.99	2139	Gen 2 is fixed
D	83.40	76.82	88.17	99.99	99.99	99.99	2189	Gen 3 is fixed
E	84.31	76.65	99.99	89.08	99.99	99.99	2199	Gen 4 is fixed
F	82.81	79.85	98.80	99.14	83.77	99.51	2200	Gen 5 is fixed
G	82.81	80.86	98.13	98.67	98.58	83.77	2212	Gen 6 is fixed

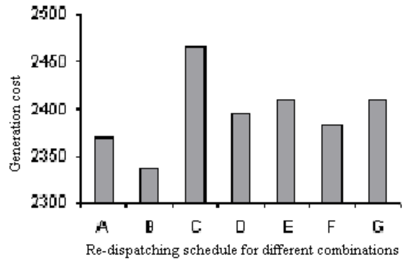

Figure 4: Generation cost for different re-dispatching schedules for 10% incremented demand.

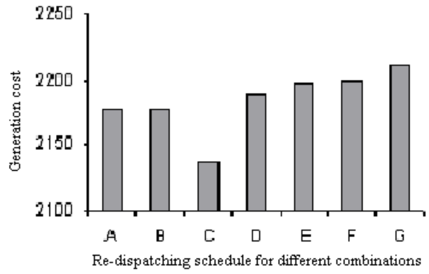

Figure 5: Generation cost for different re-dispatching schedules for 6% incremented demand.

Conclusion

This paper proposes and develops an integrated soft computing method to calculate real power generation cost and optimal allocation of the generated power in real-time under variable loading conditions. The proposed algorithm has been successfully tested to create a healthy competition between generators in different re-dispatching schedules. The load allocation of generators is generally based on Economic Theory and Optimal Power Flow concept. In the proposed method, the management of cost of generated electricity is planned as an optimization problem. The model is then implemented by changing the loading conditions of the system to produce re-dispatching generator schedule as optimal solutions using Genetic Algorithm. Case studies on IEEE 30 bus system are reported to illustrate the proposed model. With the proposed model, ISO can maintain the generation cost within predefined limit even in stressed condition. Hence the variation of electricity price can be restricted, which has awfully significant aspect in deregulated environment.

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