

Bidding Strategies for Electricity Suppliers in a Congestion Environment

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Abstract: This study presents a methodology, for bidding strategies of electricity participants in a congestion environment. This problem is modeled, as a 2 steps optimization problem. At the 1st step, a bidding strategy is solved to maximize its expected profit and at the second step, a curtailment strategy will be perform to maximize the participant's profit when the system occurs the transmission congestion. An Refined Immune Algorithm (RIA) is proposed to solve the optimization problem. RIA proposes a Scale Scheme System (SSS) to improve crossover and mutation mechanism with a competition and auto-adjust scheme by using counterweight parameter. Using this SSS algorithm, RIA has advantages and some characteristics to show a better performance than many other algorithms. The IEEE 30 Bus is selected for test. Simulation results have a good result with this standard to obtain an optimal bidding strategy for electricity suppliers under the congestion environment.

Key words: Refined immune algorithm, congestion environment, IPP, bidding strategy

INTRODUCTION

The competitive environment of electricity markets creates competition and trading mechanism for Independent Power Producers (IPPs). IPPs will use the existing transmission to sell power at a market price. IPPs are also seeking chances to be connected the lower price of existing transmission for obtaining their profits. The existing transmission owner could be considered as a 3rd party to provide the electricity wheeling for seller/buyers. The electricity wheeling cost including the congestion charges will affect the bid price of IPPs under the deregulated environments. While IPPs provide the power into the transmission system, the congestion will influence the market clearing price during the bidding process (Peng and Tomsovic, 2003).

In the pool model, the Independent System Operator (ISO) performs the power dispatch based on bids to get a market clearing price (MCP) (Hao, 2000; Zhang *et al.*, 2000). Each market participant bids its energy to expect the optimizing its own benefit. If the bidding energy makes the transmission congestion, ISO will intervene to curtail a small percentage of the bidding energy until the system is without security problems. A part of market participants will be forced to curtail the power output for satisfying the security limit. It is obvious that the benefit gained of participants is affected by the congestion. In this case, the participants have opportunities to re-submit the bids to ISO for maximizing its own benefit. It is clear

that the new economic and security problems will simultaneously occur in the competitive market. In Gountis and Bakirtzis (2004) and Rodriguez and Anders (2004), a methodology is presented for the development of bidding strategies, which the ISO makes the decisions on curtailment by considering economic and security. The electricity participants must be curtailed the transactions to meet the system security limit. At this time, the generators of some participants may be led to an unsafe operation. In fact, there are many curtailment strategies, which are derived dependent upon participants' willingness (Fang and David, 1999).

In the past, most researches have included the congestion as constraints or ignored congestion in bidding process. It is difficult to represent a practical market rule. When the congestion occurs in the markets, a noncompetitive situation will exist in the clearing price auction. Choosing a bidding process with considering congestion is complicated, especially finding the best strategy in a world of uncertainty. Mathematical methodologies used (Guan *et al.*, 2001; Lamont and Rajan, 1997; Richter and Sheble, 1998; Park *et al.*, 2001; He and Song, 2002), such as Lagrangian relation method, linear programming, game theory, etc., have been proposed to solve this problem. With the non-linearity and discrete nature considered in bidding strategy, the problem becomes more difficult to solve. Solution strategies proposed by most algorithms may be faster, they are very often limited by the problem structure and may diverge or

could lead to a local minimum. Recently, new algorithms based on the Artificial Intelligence (AI) have been developed, such as Simulated Annealing (SA) (Wong and Wong, 1996), Genetic Algorithm (GA) (Park *et al.*, 1998; Hong and Li, 2000), evolutionary programming (Nguyen and Wong, 2000; Wen *et al.*, 2003) and Immune Algorithm (IA) (Chun *et al.*, 1997, 1998; Huang, 2000). Solution strategies proposed by most AI algorithms need to consider a large solution space. Extensive numerical computation, is often required especially when the load flow technique has to be used. This study presents an Refined Immune Algorithm (RIA) based Immune Algorithms to solve the bidding strategy problems.

In this study, a maximal profit will be solved in the bidding process by use of the RIA and tabu search under deregulated environment. The bidding problem without line limit is first derived to solve the market clear price, the market clear capacity and the participants' profit by using proposed AI method. With the bidding results, the flows for each line are calculated by using the DC load flow program. When the power system occurs the congestion after the bidding process, participants will regulate the power output to meet the security constraints. A curtailment strategy will be used in the bidding process dependent upon participants' willingness. Numerical analysis will clarify congestion's influence on price and bidding strategy. The simulations have a good result with this standard and makes possible an optimal control strategy to obtain the maximal profit under security operation.

MODEL OF BIDDING STRATEGY

The pool model: The bidding problem consists of price offers and the amount of loads to be satisfied in the competitive market. The bid price curves for GenCos and DisCos are quadratic convex and concave functions, respectively. All participants submit a bidding strategy to maximize the social welfare. The model by aggregate function can be first formulated as:

$$\text{Max. Social Welfare} = \int_0^{\text{MCC}} (\lambda_d - \lambda_M) dP \quad (1)$$

Where:

- λ_M = Market Clearing Price (MCP).
- λ_d = The aggregated demand bids.
- MCC = The market clearing capacity.
- dP = Power exchange demand.

After the auction close, the MCP is determined as the price of the highest accepted bids and all power suppliers will be compensated at the MCP. Thus, the profit of GenCos can be described in Eq. (2).

$$\text{Profit}_i = \lambda_M * P_i - f(P_i) \quad (2)$$

Where:

- Profit_i = The profit of GenCo i.
- P_i = The trading power of GenCo i.
- f(P_i) = The cost function of GenCo i.

The regulation of bidding strategy due to congestion: In a pool model, GenCos submit bids to the ISO, who computes the MCP. If the power system occurs the congestion after the unconstrained dispatch, ISO will adjust the output schedule of GenCos to meet the security constraints. GenCos will be decreased the power output to relieve the congestion. A curtailment algorithm with GenCos' willingness factors is formulated as:

$$\text{Min. obj_f} = \sum_{i=1}^m \left[W_i \times (P_i - P_i^0)^2 \right] \quad (3)$$

$$\text{s.t } P_i^{\min} \leq P_i \leq P_i^{\max} \quad (4)$$

$$Lf_i^{\min} \leq Lf_i \leq Lf_i^{\max} \quad (5)$$

Where:

- W_i = Willingness factor of GenCo i for avoiding curtailment.
- P_i = The generation of GenCo i after dispatch.
- P_i⁰ = The initial generation of GenCo i.
- Lf_i = The line flow of i-th line.
- m = The number of GenCos.
- P_i^{min}, P_i^{max} = The lower and upper of power generation for GenCo i.
- Lf_i^{min}, Lf_i^{max} = The lower and upper of i-th line.

It is clear that the curtailed power will result in the lost profits of suppliers and their cost must be allocated among market participants. Thus, the new profit of GenCos can be re-written after curtailment algorithm such as Eq. (6).

$$\text{Profit}_i = \lambda_M \times P_i - f(P_i) - \Delta P_i \times W_i \times \gamma \quad (6)$$

Where:

- ΔP_i = The deviation of power dispatch for GenCo i.
- γ = The proportional factor of power dispatch.

ΔP_i is the increased/decreased output of GenCo i. If $\Delta P_i > 0$, GenCo i must increase its output. Either increasing output or decreasing output, the curtailed power must sum up to 0.

SOLUTION ALGORITHM

IA is a search algorithm, based on the mechanism of nature selection and genetics. Antigens and antibodies

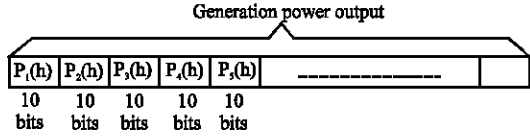


Fig. 1: Chromosome string of the antibody

can be viewed as objective functions and feasible solutions, respectively. The process of genetic structure includes crossover, mutation and reproduction. To enhance the performance of IA, a refined IA (RIA) was developed as follows.

Encoding: The coding scheme can be illustrated in Fig. 1, where each antibody indicates a combination of generation power output. The antibody is encoded as a chromosome string, which is produced by Eq. (7). When RIA search is terminated, the chromosome will then be decoded.

$$D2B \left\{ \left[\frac{P_i - P_i^{\min}}{\text{resol}_1} \right] \right\} \quad (7)$$

$$\text{resol}_1 = (P_i^{\max} - P_i^{\min}) / (2^{\text{bit}} - 1)$$

Where:

- D2B = Decimal to binary conversion.
- bit = The number of bits in a chromosome.

Affinity and diversity evaluation: Immune system generates different antibodies according to the affinity re-organization between antigens and antibodies or between 2 antibodies. There are 2 classes of affinity in IA. One is the affinity between antigens and antibodies. It represents the combination intensity between antigen and an antibody. The other one is the affinity between 2 antibodies; it shows the similarity between 2 antibodies. From Information theory, the entropy can be applied to measure diversity of antibodies. It can be computed by:

$$E^k(N) = - \sum_{i=1}^N P_{ik} \log_{10} P_{ik} \quad (8)$$

Where:

- N = Is the number of antibodies.
- P_{ik} is = The probability of the i-th allele coming out of the k-th allele.

For example, if all alleles at the k-th antibody are the same, $E^k(N) = 0$. Thus the total diversity of the k-th antibody is:

$$E(N) = \frac{1}{M} \sum_{k=1}^M E^k(N) \quad (9)$$

where, M Is the number of gene of the k-th antibody.

Two affinity forms must be taken into account in the proposed RIA. One is the affinity between 2 antibodies, i.e., j-th and k-th. It can be calculated by:

$$(\text{Aff}_b)^{jk} = (1 + E(2))^{-1} \quad (10)$$

where, E(2) is the diversity of the j-th and k-th antibody only. Note that if two antibodies are the same, $(\text{Aff}_b)^{jk}$ is equal to 1. $(\text{Aff}_b)^{jk}$ is set between 0 and 1. Another, 1 is applied to investigate the affinity between antibodies and antigens with:

$$(\text{Aff}_g)^k = (1 + \text{Obj}_f_k)^{-1} \quad (11)$$

Obj_f_k is the objective function for the k-th antibody. If 1 or more variables violate their limits, the corresponding chromosome will be put into the tabu list to avoid generating the same infeasible solution again.

Antibody re-composition: New chromosomes, will be obtained from crossover and mutation. Crossover is a structured recombination operation by exchanging genes of 2 parent antibodies. Mutation is the occasional random alteration of genes. An Improved Crossover and Mutation (ICM) scheme is proposed in this study.

Simple Crossover and Mutation scheme (SCM): The crossover process randomly (uniform distribution) selects two parents to exchange genes with a crossover rate P_c . The location of the gene within the chromosome is called locus. The crossover point is also randomly chosen from the loci. If 1 or both offspring is infeasible, another mate will be chosen again for crossover. The mutation process randomly (uniform distribution) selects one parent with a mutation rate P_m . We could randomly select a locus to mutate. If the offspring is infeasible, another parent will be chosen until a feasible solution can be obtained.

Improved Crossover and Mutation scheme (ICM): Crossover generally executes before mutation throughout searching process. In original IA, a higher crossover rate allows the exploration of solution space around the parent solution. The mutation rate controls the rate new genes are introduced and explores new solution territory. If it is too low, the solution might settle at a local optimum. On the contrary, a high rate could generate too many possibilities. The offspring lose their resemblance to the parents; the algorithm won't learn from the past and could become unstable. It is a dilemma to choose suitable crossover and mutation rate for SCM. The ICM

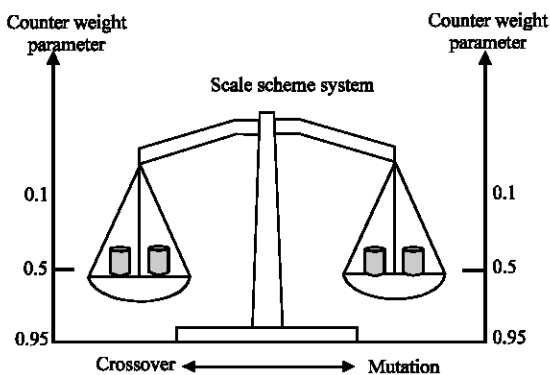


Fig. 2: Probability map of crossover and mutation in ICM for SSS = 0.5

proposes a Scale Scheme System (SSS) to improve crossover and mutation scheme for avoiding the difficulty.

- Randomly select two parents and generate offsprings by introducing SSS (g) with
 - If $Ran < SSS(g)$: use mutation.
 - If $Ran > SSS(g)$: use crossover.

where:

Rand = The uniform random number in (0,1)

SSS = $0.1 \leq SSS(g) \leq 0.95$, the control parameter with initial value set to 0.5.

g = The current generation number.

The offspring will be generated until all parents are processed. Figure 2 shows the initial relationship of crossover and mutation in ICM. If the best current solution comes from crossover, there is a more likelihood for crossover to generate better offsprings for the next population. On the contrary, there is a more likelihood for mutation to generate better offsprings. If the best solution remains the same, the operation of crossover or mutation needs to hold back. The probability of crossover and mutation is sum to 1.

- If $obj_f_{min}(g)$ comes from crossover, the control parameter SSS (g + 1) will decrease. We have

$$SSS(g+1) = SSS(g) - D \quad (12)$$

where,

$$D = \frac{|SSS(g) - SSS(g-1)|}{2}$$

In the Scale Scheme System, the counterweight D is added in crossover process such as Fig. 3. Thus, the

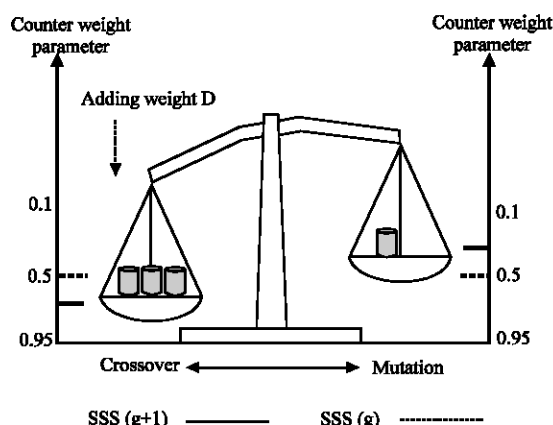


Fig. 3: The probability variation of crossover

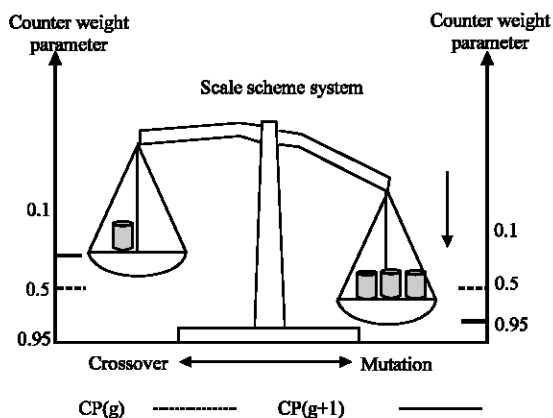


Fig. 4: The probability variation of mutation

higher probability for crossover operation will produce the next offsprings.

- If $obj_f_{min}(g)$ comes from mutation, the control parameter SSS (g + 1) will increase. We have

$$SSS(g+1) = SSS(g) + D \quad (13)$$

In SSS, the counterweight D is added in mutation process such as Fig. 4. Thus, the higher probability for mutation operation will produce the next offsprings.

- If $obj_f_{min}(g-1) = obj_f_{min}(g)$ the control parameter needs to hold back. If $SSS(g) > SSS(g-1)$, we have

$$SSS(g+1) = SSS(g) - D \quad (14)$$

else,

$$SSS(g+1) = SSS(g) + D \quad (15)$$

Tabu list: A tabu list will be constructed to define forbidden moves, such as:

- The solutions just visited except the best solution in the current generation.
- The local optima ever visited.
- The antibody violating electric constraints.

Elitism selection: The antibodies including parents and offsprings are then ranked in ascending order according to their objective function. One half of antibodies with the best value are kept as the parents for the next generation.

Stopping rule: The process of generating new antibody with the best affinity between antibody and antigen will continue until the affinity values are optimized or the maximum generation number is reached.

CASE STUDY

In this study, the IEEE 30-bus is used as examples to show the effect of the proposed method. There are 5 competitive generators (GenCos) and 20 distribution Companies (DisCos) interconnected by forty transmission lines is used for test as shown in Fig. 5. The associated cost functions for GenCos are listed in Table 1.

Generation level and MCP: To analyze the congestion's influence on the bidding strategy and price, the situation is first performed when the transmission line has not congestion. Based on GenCos and DisCos bid curves, the ISO determine a MCP after the auction close such as Fig. 6. The profits of all GenCos will be compensated at the MCP. The bid quantities and profits for GenCos can be obtained by using proposed algorithm such as in Table 2. In this study, the MCP and social welfare are 8.5669\$ and 321.726 \$/h, respectively.

The bidding strategy for GenCo1: After auction close, a DC load-flow is applied to solve for the network conditions. In our study, the line flow of line 1-2 is 301.085024 MW after DC load-flow and the system occurred the congestion. Due to the line 1-2 is overload, ISO has to curtail the power in order to keep the security operation. GenCos will be regulated the power output to relieve the congestion such as Eq. (3). From the GenCo1's view, three willingness factors are adopted to show the results as shown in Table 3. From the Table 3, if the willingness factor of GenCo1 is 4, the profit and trading power of GenCo1 are 239.4159 \$/MW and 305.9629 MW, respectively. When the willingness factor of GenCo1 increases to 8, the trading power of GenCo1 increases to 309.2864 MW and the profit of GenCo1 decreases to 239.2562 \$/h. It is obvious that the lager generation of GenCo1 will get the smaller profit due to the higher willingness factor.

Table 1: The cost function of GenCos

Generators	Cost function (\$)	P_i^{min}	P_i^{max}
GenCo1	$330 + 5.3225P_1 + 0.0045P_1^2$	200 (MW)	400 (MW)
GenCo2	$260 + 5.5025P_2 + 0.0060P_2^2$	200 (MW)	400 (MW)
GenCo3	$200 + 5.6075P_3 + 0.0070P_3^2$	200 (MW)	400 (MW)
GenCo4	$300 + 5.3055P_4 + 0.0044P_4^2$	200 (MW)	400 (MW)
GenCo5	$340 + 5.4125P_5 + 0.0060P_5^2$	200 (MW)	400 (MW)
GenCo6	$220 + 5.7035P_6 + 0.0050P_6^2$	200 (MW)	400 (MW)

Table 2: The bid quantities and profits for GenCos

	Output (MW)	Profit (\$/h)
GenCo1	360.4861	254.7761
GenCo2	255.3646	131.2665
GenCo3	211.3839	112.7822
GenCo4	370.6108	304.3505
GenCo5	262.8646	74.5868
GenCo6	286.3375	189.9459
Total	1747.0475	1067.7080

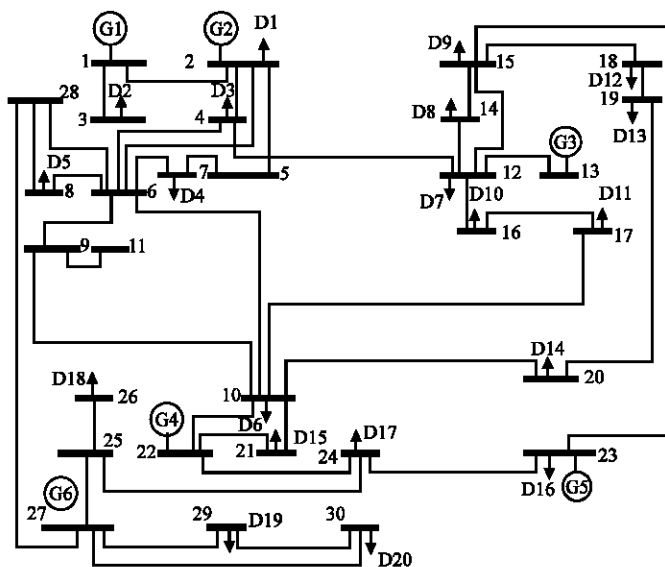


Fig. 5: The IEEE 30-bus power system

Table 3: Simulation results with three willingness factors

	GenCo1	GenCo2	GenCo3	GenCo4	GenCo5	GenCo6	Total
The profits of generators without line limited							
Profits (\$h)	254.78	131.27	112.78	304.35	74.59	189.95	1.07e+03
Output (MW)	360.47	255.37	211.39	370.61	262.86	286.34	1.74e+03
The profits of generators under different willingness factor							
Profits (\$h)	237.16	128.91	107.52	302.10	72.21	187.94	1.04e+03
Output (MW)	299.90	273.70	237.54	349.95	281.33	304.62	1.75e+03
W (\$/MW)	2	2	2	2	2	2	
Profits (\$h)	239.42	130.97	112.22	303.98	65.51	189.51	1.04e+03
Output (MW)	305.96	249.66	219.16	377.91	300.29	294.07	1.75e+03
W (\$/MW)	4	2	2	2	2	2	
Profits (\$h)	239.26	118.45	112.68	304.18	74.44	189.85	1.04e+03
Output (MW)	309.29	300.10	214.08	375.17	259.24	289.18	1.75e+03
W (\$/MW)	8	2	2	2	2	2	

Table 4: Convergence test

Algorithm	Maximal converged deviation	Minimal converged deviation	Average converged deviation
GA	$2.524 \times 10^*$	$2.514 \times 10^*$	$2.519 \times 10^*$
IA	$2.483 \times 10^*$	$2.494 \times 10^*$	$2.487 \times 10^*$
RIA	$1.184 \times 10^*$	$1.163 \times 10^*$	$1.175 \times 10^*$

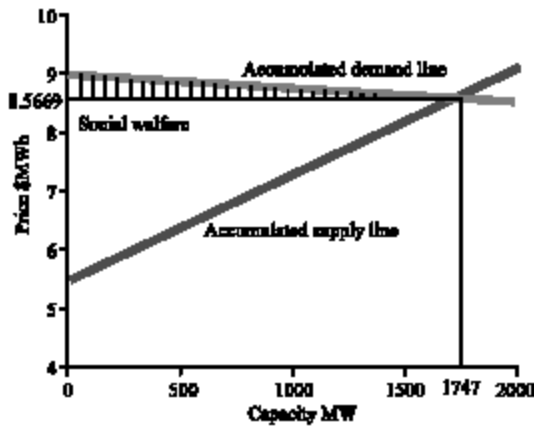


Fig. 6: The accumulated bids curves of GenCos and DisCos

Figure 7 shows the bidding strategy surface of GenCo1. By considering the transmission congestion, the bidding strategy of GenCo1 is required to adopt a desired willingness factor in order to get a higher expected profit. If the GenCo1 considers the operation security of units, the higher willingness factor will get the more bids to output the power. It can be shown that the optimal bidding strategy for GenCo1 is recommend in Fig. 7.

Convergence test: Figure 8 illustrates the convergence characteristics of RIA, IA and GA. It shows the improvement of the RIA over GA and IA. An IBMPC with P-IV 2.2 GHz CPU and 512 MB SDRAM is used in our test. Table 4 shows the maximum, minimum and average optimized deviation with 100 random initial parents tested. The population size of each trial is 30. Although, the solution improvement is subtle, it did show the capability of RIA in exploring a more likely global optimum.

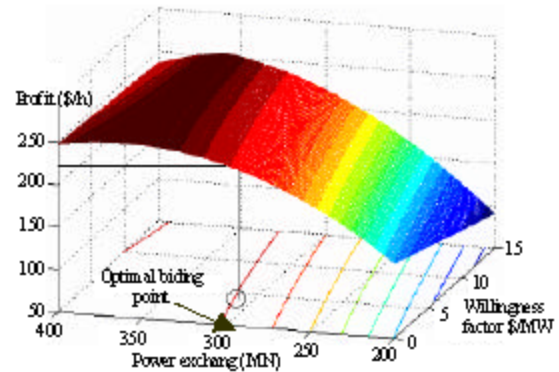


Fig. 7: The bidding strategy surface of GenCo1

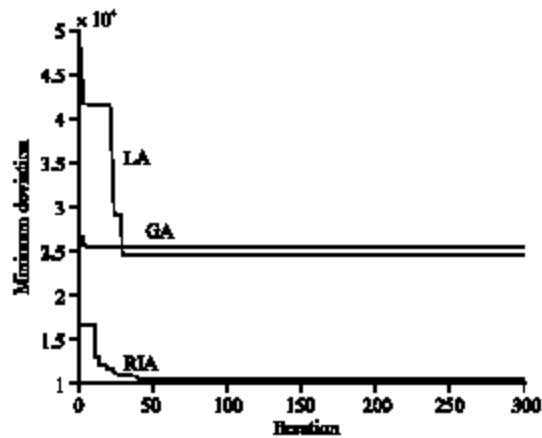


Fig. 8: The convergence characteristics of RIA, IA and GA

CONCLUSION

This study presents a bidding strategy of electricity suppliers in a congestion environment. The model by aggregate function is used to solve the MCP for determining the electricity output of all participants. A curtailment algorithm is formulated to perform the congestion management. In this approach, GenCos can try to maximize its profit by considering their curtailed

willingness and their system security. RIA is adopted to solve the optimal problem. The methodology has been tested on IEEE 30-Bus system and has proved effective in finding the optimal bidding strategy. The effective of RIA has been successfully demonstrated by numerical example. RIA has great potential to be further applied to many ill-conditioned problems in power system planning and operations.

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