World Academy of Science, Engineering and Technology
International Journal of Electrical and Computer Engineering
Vol:2, No:8, 2008

GEP Considering Purchase Prices, Profits of IPPs and Reliability Criteria Using Hybrid GA and PSO

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***Abstract*—**In this paper, optimal generation expansion planning (GEP) is investigated considering purchase prices, profits of independent power producers (IPPs) and reliability criteria using a new method based on hybrid coded Genetic Algorithm (GA) and Particle Swarm Optimization (PSO). In this approach, optimal purchase price of each IPP is obtained by HCGA and reliability criteria are calculated by PSO technique. It should be noted that reliability criteria and the rate of carbon dioxide (CO_2) emission have been considered as constraints of the GEP problem. Finally, the proposed method has been tested on the case study system. The results evaluation show that the proposed method can simply obtain optimal purchase prices of IPPs and is a fast method for calculation of reliability criteria in expansion planning. Also, considering the optimal purchase prices and profits of IPPs in generation expansion planning are caused that the expansion costs are decreased and the problem is solved more exactly.

Keywords--GEP Problem, IPPs, Reliability Criteria, GA, PSO.

I. INTRODUCTION

RECENTLY, regarding growing of the load growth and subsequent more generation demand, generation expansion planning (GEP) has been important issue. The main goal of GEP is to minimize the network generation and operational costs while meeting imposed technical, economic and reliability constraints. GEP should be provided an adequacy supply of electrical energy for the network loads during the planning horizon year (target year) [1]. The generation expansion planning problem is a non-linear and complex problem. Thus, various methods such as genetic algorithm, expert systems, fuzzy logic, artificial neural networks, decomposition method and simulated annealing have been proposed to solve the problem in traditional environments [2-4]. In private conditions, the utility companies have many options for constructing the new generating plants. One of them is introducing the independent power producers (IPPs) [5-8]. According to the Kyoto Protocol, the value of poisonous gas emission should be limited according to some standard levels. Thus, the environment maintenance and therefore green generation is an important subject that should be considered in generation expansion by utility companies [5-7].

Reliability of power supply has always been an important issue in the electric power systems. Providing the uninterrupted electric power with high quality is essential for development of a country economically and industrially. The methods of calculating the reliability criteria can be classified as analytical and simulation methods [9]. Calculation and assessment of reliability criteria in a large power system by these methods is time consuming. Thus, for calculation of these parameters it is suitable a fast method can be developed. In [10], the GEP problem has been solved considering competing electricity market and reliability criteria using game theory, but environmental emission has not been studied. In Ref. [5-8], the GEP problem has been studied in a restructured environment. However, optimal purchase price of IPPs has not been investigated in this literature.

In this paper, the GEP problem has been studied from the utility company view point considering purchase price of IPPs and reliability criteria using hybrid coded Genetic Algorithm (HCGA) and Particle Swarm Optimization (PSO) technique. The goal is to minimize the utility company costs while satisfying the acceptable values for IPP profit, CO_2 emission limits and reliability criteria. In the proposed approach, HCGA is used for obtaining the optimal purchase price of IPPs and the reliability criteria are calculated by PSO technique. The results evaluation reveals that the proposed approach can simply presents optimal purchase prices of IPP and is a fast method for calculation of reliability criteria.

This paper is organized as follows: optimal generation expansion planning problem considering IPPs is represented in Sec. 2. Section 3 describes the problem formulation. Hybrid coded genetic algorithm and chromosome structure of the problem is given in Sec. 4. Sec. 5 describes completely particle swarm optimization. Calculation method of reliability criteria and GEP considering reliability constrains are represented in Sec. 5 and 6, respectively. The characteristics of case study system and simulation results are given in Sec. 7. Finally, in Sec. 8 conclusion is illustrated.

II. OPTIMAL GEP PROBLEM CONSIDERING IPPS

Before formulation of the optimal GEP problem considering IPPs, several assumptions are considered as follows:

1) Annual load demand and peak load are specified at the planning horizon year (expansion time).
2) Generation technologies include nuclear, coal, oil and gas generations.

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3) IPPs are classified as basic, middle and peak type.
4) The capacity and maximum number of units for each generation technology and type of IPPs are given.
5) The limit of CO_2 emission and reliability criteria are specified.

In order to decrease the cost of generation planning, generation technologies and IPPs should be arranged from cheapest to the most expensive variable cost (suitable arrangement) under inverse function of load duration curve (LDC) [5-7]. The schematic of inverse function of load duration curve (LDC) at the planning horizon year has been shown in Fig. 1. Regarding the fact that variable costs of IPPs are lower than relevant generations, but the suitable arrangement for generating plants from variable costs view point is nuclear (N) generation, basic-type (BT) IPP, coal (C) generation, middle-type (MT) IPP, oil (O) generation, peak-type (PT) IPP and finally gas (G) generation, respectively.

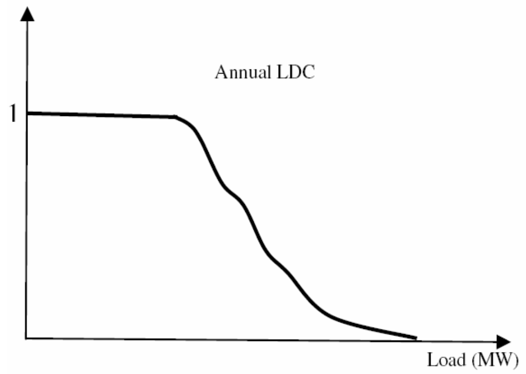

Fig. 1. Schematic of inverse function of LDC at planning horizon year

III. Problem Formulation

The goal of the optimal GEP is minimizing the total utility cost (investment and operation costs) and the purchased energy costs of IPPs. Thus, the objective function is defined as follows:

$$Min\left\{\sum_{i=1}^{M}(\omega_{si}a_i\Delta x_i+\omega_{mi}b_iQ_i)+\sum_{j=1}^{nipp}(\omega_{kj}P_jQ_j)\right\} \tag{1}$$

Where:
i: An indicator for unit type.
M: Total number of generation technologies for utility company.
ω_{si}: Weighted coefficient of fixed cost of i^{th} units.
a_i: Fixed cost (\$/MW) of i^{th} units.
Δx_i: Additional capacity of i^{th} units (MW).
ω_{mj}: Weighted coefficient of variable cost of i^{th} units.
b_i: Variable cost (\$/MWh) of i^{th} units.
Q_i: Annual generated power of i^{th} units at the planning horizon year (MWh).
j: An indicator for IPP type.
$nipp$: Total number of IPPs.
ω_{kj}: Weighted coefficient of purchase price of j^{th} IPP.
P_j: Purchase price for power energy of j^{th} IPP (\$/MWh).
Q_j: Annual generated power of j^{th} IPP at the planning horizon year (MWh).

Several restrictions have to be modeled in a mathematical representation to ensure that the mathematical solutions are in line with the planning requirements. These constraints are as follows:

$$\Delta x_i = uc_i.nu_i \qquad i=1,2,...,N \tag{2}$$

$$nu_{i\min} \le nu_i \le nu_{i\max} \qquad i=1,2,...,N \tag{3}$$

$$\sum_{i=1}^{M}x_i+\sum_{j=1}^{3}x_j \ge P_D+P_R \tag{4}$$

$$profit_i > 0 \qquad i=1,...,nipp \tag{5}$$

$$x_i = x_{i0}+\Delta x_i \qquad i=1,2,...,N \tag{6}$$

$$X_0=0, X_i=\sum_{k=1}^{i}x_k \qquad i=1,2,...,N \tag{7}$$

$$Q_i = 8760\int_{X_{i-1}}^{X_{i-1}+x_i}L_T(u)du \qquad i=1,2,...,N \tag{8}$$

$$Q_{i\min} \le Q_i \le Q_{i\max} \qquad i=1,2,...,N \tag{9}$$

$$\sum_{i=1}^{N}(E_iQ_i) \le L_{CO_2} \tag{10}$$

$$LOLP \le LOLP_{\max} \tag{11}$$

$$EENS \le EENS_{\max} \tag{12}$$

where, N=M+nipp and:
uc_i: Capacity of i^{th} unit (MW).
nu_i: Number of new i^{th} units.
x_i: capacity of existed i^{th} units (MW).
x_{i0}: Initial existed capacity of i^{th} units (MW).
X_i: Cumulative capacity from 1^{th} to i^{th} units (MW).
$profit_i$: Profit of i^{th} IPP (\$).
P_D: Peak load at the planning horizon year (MW).
P_R: Supply reservation at the planning horizon year (MW).
$L_T(u)$: Inverse function of LDC supplied by utility at the planning horizon year.
E_i: Carbon dioxide emission (CO_2) generated by i^{th} unit (Ton/MWh).
L_{CO_2} : Limit of CO_2 emission.
$LOLP$: Loss of load probability.
$EENS$: Expected energy not supplied.

IPP profit is determined by balance point analysis approach (see Appendix A for more details). LOLP and EENS are considered as reliability criteria in this paper.

IV. HCGA and Chromosome Structure of the Problem

The standard genetic algorithm is a random search method that can be used to solve non-linear system of equations and optimize complex problems. The base of this algorithm is the selection of individuals. It does not need a good initial estimation for sake of problem solution, In other words, the solution of a complex problem can be started with weak initial estimations and then be corrected in evolutionary process of fitness [12]. The standard genetic algorithm manipulates the binary strings which may be the solutions of the problem. The genetic algorithm generally includes the three fundamental genetic operators of reproduction, crossover and mutation. These operators conduct the chromosomes toward better fitness. Although binary codification is conventional in genetic algorithm, but real and decimal coded genetic algorithms have been also used to solve some problems in [13] and [14] respectively.

Due to this fact that variables are combination of integer and real parameters, in this study, combination of the decimal and real coded genetic algorithm is used to solve the GEP problem. In this method, crossover can take place only at the boundary of two random variables. Mutation operator selects one of existed random variables in chromosome and then changes its value randomly. Reproduction operator, similar to standard form, produces each chromosome proportional to value of its objective function. Thus, the chromosomes which have better objective functions will be selected more probable than other chromosomes for the next population (Elitist strategy). The chromosome is defined as an array of random variables:

$$y = [\, nu_1 \quad nu_2 \quad \dots \quad nu_N \quad P_1 \quad \dots \quad P_{nipp}\,] \tag{13}$$

Similar to [13], a new mutation operator, called class mutation is used and the random variables are divided two different groups (nu_i and P_i) for class mutation operation. The speed of convergence increases using of mentioned approach.

V. Particle Swarm Optimization

Particle swarm optimization algorithm, which is tailored for optimizing difficult numerical functions and based on metaphor of human social interaction, is capable of mimicking the ability of human societies to process knowledge [15]. It has roots in two main component methodologies: artificial life (such as bird flocking, fish schooling and swarming); and, evolutionary computation. Its key concept is that potential solutions are flown through hyperspace and are accelerated towards better or more optimum solutions. Its paradigm can be implemented in simple form of computer codes and is computationally inexpensive in terms of both memory requirements and speed. It lies somewhere in between evolutionary programming and the genetic algorithms. As in evolutionary computation paradigms, the concept of fitness is employed and candidate solutions to the problem are termed particles or sometimes individuals, each of which adjusts its flying based on the flying experiences of both itself and its companion. It keeps track of its coordinates in hyperspace which are associated with its previous best fitness solution, and also of its counterpart corresponding to the overall best value acquired thus far by any other particle in the population. Vectors are taken as presentation of particles since most optimization problems are convenient for such variable presentations. In fact, the fundamental principles of swarm intelligence are adaptability, diverse response, proximity, quality, and stability. It is adaptive corresponding to the change of the best group value. The allocation of responses between the individual and group values ensures a diversity of response. The higher dimensional space calculations of the PSO concept are performed over a series of time steps. The population is responding to the quality factors of the previous best individual values and the previous best group values. The principle of stability is adhered to since the population changes its state if and only if the best group value changes. As it is reported in [16], this optimization technique can be used to solve many of the same kinds of problems as GA, and does not suffer from some of GAs difficulties. It has also been found to be robust in solving problem featuring non-linearing, non-differentiability and high-dimensionality. PSO is the search method to improve the speed of convergence and find the global optimum value of fitness function.

PSO starts with a population of random solutions ‘‘particles’’ in a D-dimension space. The *i*th particle is represented by $X_i = (x_{i1}, x_{i2}, \dots, x_{iD})$. Each particle keeps track of its coordinates in hyperspace, which are associated with the fittest solution it has achieved so far. The value of the fitness for particle *i* (pbest) is also stored as $P_i = (p_{i1}, p_{i2}, \dots, p_{iD})$. The global version of the PSO keeps track of the overall best value (gbest), and its location, obtained thus far by any particle in the population. PSO consists of, at each step, changing the velocity of each particle toward its pbest and gbest according to Eq. (14). The velocity of particle *i* is represented as $V_i = (v_{i1}, v_{i2} \dots v_{iD})$. Acceleration is weighted by a random term, with separate random numbers being generated for acceleration toward pbest and gbest. The position of the *i*th particle is then updated according to Eq. (15) [15, 16].

$$v_{id}(t+1) = w \times v_{id}(t) + c_1 r_1 (P_{id} - x_{id}(t)) + c_2 r_2 (P_{gd} - x_{id}(t)) \tag{14}$$

$$x_{id}(t+1) = x_{id}(t) + c v_{id}(t+1) \tag{15}$$

Where, P_{id} and P_{gd} are *pbest* and *gbest*. It is concluded that *gbest* version performs best in terms of median number of iterations to converge. However, *Pbest* version with neighborhoods of two is most resistant to local minima. The results of past experiments about PSO show that ω was not considered at an early stage of PSO algorithm. However, ω affects the iteration number to find an optimal solution. If the value of ω is low, the convergence will be fast, but the solution will fall into the local minimum. On the other hand, if the value will increase, the iteration number will also increase and therefore the convergence will be slow. Usually, for running the PSO algorithm, value of inertia weight is adjusted in training process. It was shown that PSO algorithm is further improved via using a time decreasing inertia weight, which leads to a reduction in the number of iterations [17].

In Eq. (14), term of $c_1 r_1 (P_{id} - x_{id}(t))$ represents the individual movement and term of $c_2 r_2 (P_{gd} - x_{id}(t))$ represents the social behavior in finding the global best solution.

VI. Calculation Method of Reliability Criteria

PSO is used as a sampling tool to construct the generation system state array. Every generation unit has its own forced outage rate (FOR). The probability of each unit down is equal to its FOR. The total number of states for all possible combinations of *n* generating units in the system is $K=2^n$. The PSO reduces this state space and converts it to a small fraction of K. Population of the PSO is consisted of several individuals (particle). Each particle represents a system state. Length of any particle (*npar*) is equal to the total number of system generators. Following steps are used to determine reliability criteria by PSO algorithm:

1) An initial population is created randomly by a specified number of individuals (particle).
2) For particle j, probability ($prob_j$), capacity (Cap_j), total number of equivalent permutations ($copy_j$) and

interruption duration (Δt_j) are calculated as follows [11]:

$$prob_j = \prod_{k=1}^{tn} gp_k \tag{16}$$

$$Cap_j = \sum_{k=1}^{tn} s_k c_k \tag{17}$$

$$copy_j = \binom{L_1}{O_1}\binom{L_2}{O_2}\cdots\binom{L_N}{O_N} \tag{18}$$

$$\Delta t_j = L_T(Cap_j) \tag{19}$$

$$eu_i = iu_i + nu_i \tag{20}$$

where: $tn = \sum_{i=1}^{N} eu_i$ and:

c_i: Generation capacity of i^th unit.
iu_i: Initial number of i^th units.
eu_i: number of existed i^th units.
tn: Total number of units.

In Eq. (17), s_k is the value of the binary number that describes state of generation unit. If k^{th} unit is online, the value of this parameter is equal to 1 (s_k=1), otherwise it is zero (s_k=0). In Eq. (16), gp_k describes state probability of generation unit and its values are determined as follows:

if s_k=1 $\quad gp_k = 1 - FOR_k$

if s_k=0 $\quad gp_k = FOR_k$

In Eq. (18), O_K is the number of ones in k^{th} part of a chromosome with length of L_k.

3) The fitness of particle is calculated according to (21).

$$Fit_j = 1/(copy_j.prob_j) \tag{21}$$

4) If $Cap_j < P_{D_j}$, a fail state happens and is stored in array.

5) If end condition is satisfied, reliability criteria are calculated using saved data in the state array as follows:

$$LOLP = \sum_{j=1}^{Z} (prob_j.copy_j.\Delta t_j) \tag{22}$$

$$EN_j = (prob_j.copy_j).8760 \int_{Cap_j}^{P_D} L_T(u)du \qquad j = 1...Z \tag{23}$$

$$EENS = \sum_{j=1}^{Z} EN_j \tag{24}$$

Where: Z is total number of saved states. EN is supplied energy for saved j^{th} state.

VII. GEP Considering Reliability Constrains

Combination of GA and PSO are applied to solve the generation expansion planning program so that reliability criteria are determined under their limits. GEP problem is solved and optimized by GA to minimize the total cost of utility as shown in Eq. (1). But reliability criteria are calculated using PSO for best individual after specific iterations of GA. The specific iterations have been considered 500 in this study. If reliability criteria do not satisfied their limits, weighted coefficients are reformed in objective function. The selection probability of units with high reliability (units with lower FORs) is increased by reducing their weighted coefficients (ω_{si}, ω_{mi} and ω_{ki}). The flowchart of the proposed approach is summarized in Fig. 2.

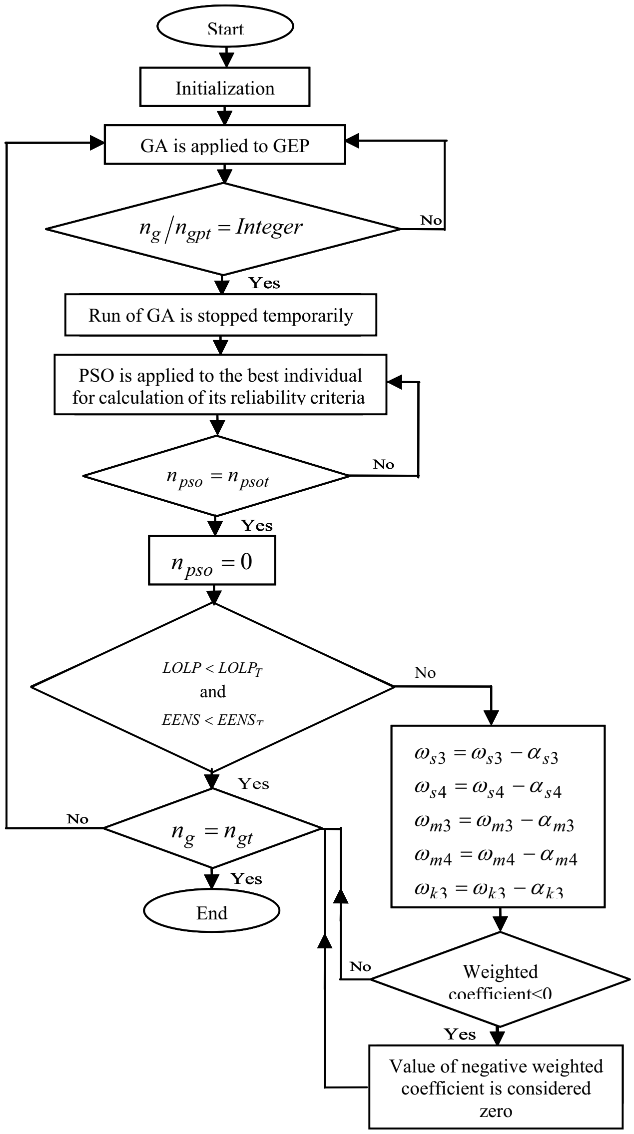

Fig. 2. The flowchart of the proposed approach

where:
n_g: A counter for number of produced generations in GA.
n_{gt}: Number of produced generations in GA.
n_{pso}: A Counter for number of produced generations in PSO.
n_{psot}: Number of produced generations in PSO.
n_{gpt}: Required n_{gt} to run of PSO.
α_{si}, α_{mi} and α_{ki} are reduction factors of ω_{si}, ω_{mi} and ω_{ki}, respectively.

Decreasing the weighted coefficient is made for oil, gas and peak type IPP units, because they have lower failure rates than other units. A unit with smallest FOR has largest reduction in its weighted coefficient. Reduction factors can be determined with respect to the initial value of weighted coefficients. In this study, the reduction factors are fraction of considered unit's FORs. (see Appendix B for more details).

VII. CASE STUDY

The proposed method has been applied to an example system, which is a modification from as given in Ref. [5-7]. In this study, peak load, reserve power, $LOLP_{max}$ and $EENS_{max}$ have been considered 15600 MW, 1000 MW, 0.04 and 9000 MWh (0.0089 percent of the whole needed energy), respectively. Also, due to inverse function of annual LDC, an analytical function is defined as follows:

$$L_T(x) = \left(\frac{(h_1-1)}{h_2}x+1\right)\left(u(x)-u(x-h_2)\right)+h_1 e^{-\left(\frac{x-h_2}{h_3}\right)^2} u(x-h_2) \quad (25)$$

Where, h_1, h_2 and h_3 are equal to 0.9802, 7600 and 4685.4 respectively, and u(x) is a step function. Also, CO_2 emission limit is 3×10^7 (Ton). The initial values of weighted coefficients are considered 1. The required data for generation technologies of utility and different types of IPPs are listed in Tables 1 and 2.

TABLE I
DATA FOR GENERATION TECHNOLOGY OF UTILITY

Unit Type	Unit Capacity (MW)	Fixed Cost ($/KW)	Variable cost ($/MWh)	CO2 coefficient (Ton/ MWh)	Existing number	F.O.R
N	1000	360	10	0	3	0.04
C	500	250	24	0.33	4	0.035
O	200	155	47	0.28	7	0.025
G	150	115	60	0.21	10	0.02

TABLE II
DATA OF IPPS

IPP Type	Unit Capacity (MW)	Fixed Cost ($/KW)	Variable cost ($/MWh)	CO2 coefficient (Ton/ MWh)	Existing number	F.O.R
BT	500	240	15	0.35	0	0.04
MT	300	193.3	34	0.25	0	0.035
PT	150	133.3	52	0.21	0	0.03

The proposed approach is tested on the case study system and the results are given in Tables 3 and 4. Table 3, describes the number of new units of each generation technology which must be added to power system at the planning horizon year. Also, optimal purchase prices of IPPs and related profits are listed in Table 4.

TABLE III
NEW GENERATION CAPACITY

Unit Type	Number of new units	Capacity of each unit
N	1	1000
C	0	500
O	5	200
G	11	150
BT of IPP	6	500
MT of IPP	2	300
PT of IPP	10	150

TABLE IV
OPTIMAL PURCHASE PRICES AND PROFILE OF IPPS

IPP Type	Optimal Purchase Price ($/MWh)	Profit ($)
BT	42.812	423790
MT	59.85	654780
PT	103.44	336060

Due to Table 4, as expected, the optimal purchase prices of base-type, middle-type and peak-type of IPPs have been obtained from lowest to highest rate, respectively. Profits of IPPs are greater than zero and acceptable. Also, the utility cost and CO_2 emission are obtained 3.9923×10^9 ($) and 2.0692×10^7 (Ton) (lower than its limit). Moreover, it should be noted that if purchase prices of IPPs are different from optimal purchase prices, the utility cost will be increased. According to Figs 3 and 4, reliability criteria are decreased by increasing of GA iterations.

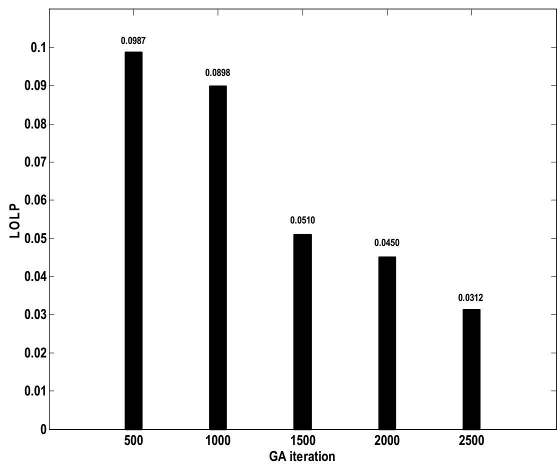

Fig. 3. LOLP versus GA iterations

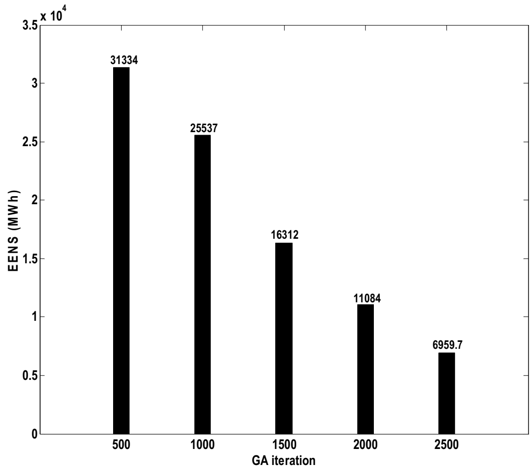

Fig. 4. EENS versus GA iterations

Regarding to optimal purchase prices and profits of IPPs, It can be concluded that IPPs may play important role in electricity market. Finally LOLP and EENS that have been considered as the reliability constraints in GEP, are obtained 0.0312 and 6959.7 MWh, respectively.

IX. CONCLUSION

In this paper, optimal generation expansion planning in restructured power system has been studied using the hybrid coded genetic algorithm and particle swarm optimization. Moreover, independent power producer's contribution and two reliability criteria (LOLP and EENS) have been considered in

GEP problem. The proposed approach is a fast method for calculation of reliability criteria and can simply obtain optimal purchase prices for different types of IPP. According to simulation results it is concluded that IPPs play important role in generation expansion planning and subsequent in competing electricity market. Thus, considering optimal purchase prices and profits of them can be caused that the expansion costs are decreased and GEP problem is solved more precisely. Also, regarding to the optimal purchase prices and profits of IPPs, it can be said that the optimal purchase prices of base-type, middle-type and peak-type of IPPs are obtained from lowest to highest rate, respectively. Finally, it can be concluded that in the proposed method, reliability criteria of LOLP and EENS are decreased by increasing of GA iterations.

APPENDIX

A. Balance point analysis for IPP

Balance point analysis describes relations among profit, costs, pricing politic and generation rate. Financial manager can maximize company profit by determining of the price, generation approaches and generation rate. Balance point analysis is related to the following problems:

- Analysis of profit variation considering variation of sale volume (structure of costs and generation price is fixed).
- Analysis of profit variation considering variation of costs and prices.

If the sale income is subtracted from total costs (fixed and variable costs), the company profit is determined. In other words, company profit is started after balance point and this profit is increased by rising of company generation. Fig. 5 represents the balance point analysis for an independent power producer. In the balance point analysis, $Q = Q_{min}$, Loss=0 and Profit=0.

Due to Fig. 5, following equations are obtained:

$$CI_j = a_j \Delta x_j + b_j Q_j \qquad j = 1, \ldots, nipp \tag{26}$$

$$CT_j = P_j Q_j \qquad j = 1, \ldots, nipp \tag{27}$$

$$profit_j = CT_j - CI_j \qquad j = 1, \ldots, nipp \tag{28}$$

Where:
CI_j *($)*: Total cost of j^{th} IPP
CT_j *($)*: Income of j^{th} IPP

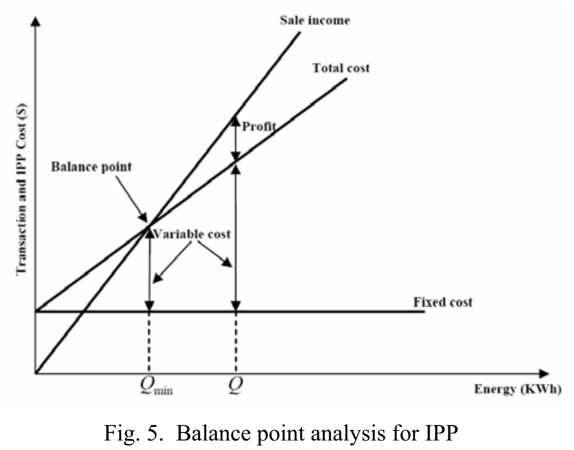

Fig. 5. Balance point analysis for IPP

Minimum value of purchased energy for j^{th} IPP is calculated with following equation:

$$Q_{j\,min} = \frac{a_j \Delta x_j}{P_j - b_j} \tag{29}$$

B. Reeducation factors

$\alpha_{s3} = 0.25$
$\alpha_{s4} = 0.3$
$\alpha_{m3} = 0.25$
$\alpha_{m4} = 0.3$
$\alpha_{k3} = 0.2$

C. Some data of HCGA program

The crossover rate (P_c) =0.7
The mutation rate (P_m) =0.15
Population size =50
Maximum number of generations (n_{gt}) =2500

D. Some data of PSO program

C_1=1.5
C_2=1.5
Population size=100
Maximum number of generations (n_{psot}) =50

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