Journal of Zhejiang University SCIENCE A
ISSN 1673-565X (Print); ISSN 1862-1775 (Online)
www.zju.edu.cn/jzus; www.springerlink.com
E-mail: jzus@zju.edu.cn

GA and PSO culled hybrid technique for economic dispatch problem with prohibited operating zones

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Received Dec. 27, 2006; revision accepted Mar. 21, 2007

Abstract: This paper presents an efficient and reliable genetic algorithm (GA) based particle swarm optimization (PSO) technique (hybrid GAPSO) for solving the economic dispatch (ED) problem in power systems. The non-linear characteristics of the generators, such as prohibited operating zones, ramp rate limits and non-smooth cost functions of the practical generator operation are considered. The proposed hybrid algorithm is demonstrated for three different systems and the performance is compared with the GA and PSO in terms of solution quality and computation efficiency. Comparison of results proved that the proposed algorithm can obtain higher quality solutions efficiently in ED problems. A comprehensive software package is developed using MATLAB.

Key words: Economic dispatch (ED), Genetic algorithm (GA), Particle swarm optimization (PSO), Hybrid GAPSO, Prohibited operating zone, Crossover, Mutation, Velocity
doi:10.1631/jzus.2007.A0896 **Document code:** A **CLC number:** TM73

INTRODUCTION

Efficient scheduling of available energy resources for satisfying load demand has become an important task in modern power systems. Economic dispatch (ED) problem is one of the fundamental issues in modern power system operation. It is an optimization problem and its objective is to reduce the total generation cost of units, while satisfying all the system constraints (Wood and Wallenberg, 1984). Previous efforts in solving ED problems employed various mathematical programming methods and optimization techniques. These conventional methods include the lambda-iteration method, the base point and participation factors method and the gradient method (Wood and Wallenberg, 1984; Lee and Breipohl, 1993; Yoshida *et al*., 2000). In all the above methods, the essential assumption is that the incremental cost curves of the units are monotonically increasing piecewise-linear functions. But this assumption may render these methods infeasible because of the non-linear characteristics in practical systems. The non-linear characteristics of a generator include discontinuous prohibited operating zones, ramp rate limits and cost functions which are not smooth or convex. Several researches were conducted in the ED field in the past two decades. A dynamic programming (DP) method for solving the ED problem with valve point loading was presented by Lee and Breipohl (1993). However, the DP method may cause the dimensions of the ED problem to become extremely large, thus requiring enormous computational efforts. The artificial intelligence techniques such as Hopfield neural networks have been employed to solve the ED problem for units with piecewise quadratic fuel cost functions and prohibited operating zones (Yalcinoz and Short, 1998). But an unsuitable sigmoidal function adopted in the Hopfield model may suffer from excessive numerical iterations, resulting in huge calculations. Genetic algorithms are adaptive search techniques based on the principles and mechanisms of natural selection and “survival of the fittest" from natural evolution. The GA method has been successfully used to solve power optimization problems such as feeder configuration and capacitor placement in a distribution system (Walters and Sheble, 1993). Due to its high potential for global optimization, GA has received great attention for solving ED problems. Walters and Sheble (1993) presented a GA model employing units output as the encoded parameter of chromosome to solve an ED problem for valve point discontinuities. Chen and Chang (1995) presented a GA method using the system incremental cost as encoded parameter for solving ED problems that can take into account network losses, ramp rate limits, and valve point zone. An integrated GTS algorithm incorporating GA, Tabu search and simulated annealing for the ED problem was presented by Fung *et al*.(2000). Even though GA methods have been employed successfully to solve complex optimization problems, recent research has identified some deficiencies in GA performance (Michalewicz, 1994). If the problem has epistemic objective function (where the parameters being optimized are highly correlated), the GA efficiency is degraded and the premature convergence of GA to a local optimal solution is also possible (Mantawy *et al*., 1999). The possibility of solving the economic dispatch problem by applying refined genetic algorithm was developed by Sheble and Brittig (1995). Song and Xuan (1998) presented a new combined heat and power economic dispatch algorithm using genetic algorithm by penalty function method. Wong and Wong (1994) provided a rational model by considering the economic dispatch of thermal units for the demand by genetic algorithm and simulated annealing techniques.

Particle swarm optimization (PSO), first introduced by Kennedy and Eberhart (1995), is one of the modern heuristic algorithms. It was developed through simulation of a simplified social system, and has been found to be robust in solving continuous non-linear optimization problems. The PSO technique can generate high-quality solutions within shorter calculation time and have more stable convergence characteristics than other stochastic methods (Yoshida *et al*., 2000; Gaing, 2003; Zhao *et al*., 2005; Huang *et al*., 2005). Unlike in GA method, in PSO the selection operation is not performed (Gaing, 2003; Zhao *et al*., 2005). All the particles in PSO are kept as members of the population through the course of a run (a run is defined as the total number of generation of the evolutionary algorithms prior to termination) (Gaing, 2003). It is the velocity of the particle, which is updated according to the previous best position of its companions. The particles fly with the updated velocities. Although the PSO is seemingly sensitive to the tuning of some weights or parameters, many researches are still in progress for proving its potential in solving complex power system problems. Gaing (2003) applied PSO method for solving the ED problem considering the generator constraints. Zhao *et al*.(2005) applied multi-agent based PSO for solving optimal reactive power dispatch problem. Huang *et al*.(2005) applied PSO for solving short term load forecasting problem. Victoire and Jeyakumar (2005) integrated PSO with sequential quadratic programming for solving dynamic dispatch problem with valve point effects.

In this paper, a PSO method is integrated with GA for solving ED problem in power system. The proposed method considers the non-linear characteristics of a generator such as ramp rate limits and prohibited operating zone for actual power system operation. The proposed method is applied to three different systems and the solutions obtained are compared with the real coded GA method and PSO method. The reliability of the proposed algorithm is demonstrated in the aspects of solution quality and computation efficiency. The paper is organized as follows. In Section 2, the problem formulation for ED problem with all constraints is presented. Section 3 explains the concept of particle swarm optimization and its operators. Implementations of GA and PSO in the proposed hybrid GAPSO algorithm are given in Section 4. The proposed hybrid GAPSO algorithm, which is a hybrid of PSO method and GA method, is applied for the test cases and simulation results are discussed in Section 5 and conclusions are summarized in Section 6.

PROBLEM FORMULATION

The objective of ED problem is to simultaneously minimize the generation cost rate and to meet the load demand of a power system over some appropriate period while satisfying various constraints (Walters and Sheble, 1993).

The objective function is

$$F_{\mathrm{T}} = \sum_{i=1}^{n} F_i(P_i) = \sum_{i=1}^{n} (A_i P_i^2 + B_i P_i + C_i). \quad (1)$$

Constraints are:

(1) Power balance equation

$$\sum_{i=1}^{n} P_i = P_{\mathrm{D}} + P_{\mathrm{L}}. \quad (2)$$

(2) Ramp rate limits

For convenience in solving the ED problem, the unit generation output is usually assumed to be adjusted smoothly and instantaneously. But in practical situations, the operating range of all online units is restricted by their ramp rate limits for forcing the units operation continually between two adjacent specific operation periods (Lee and Breipohl, 1993; Walters and Sheble, 1993). The inequality constraints due to ramp rate limits for unit generation changes are given below:

(i) As generation increases,

$$P_i - P_i^0 \le R_{\mathrm{u}i}; \quad (3)$$

(ii) As generation decreases,

$$P_i^0 - P_i \le R_{\mathrm{d}i}. \quad (4)$$

Where P_i is the current output power and P_i^0 the previous output power; $R_{\mathrm{u}i}$ and $R_{\mathrm{d}i}$ are the up and down ramp limit of the ith generator, respectively.

(3) Prohibited operating zone

The prohibited operating zones in the input-output curve of the generator are due to steam valve operation or vibration in its shaft bearing. Because it is difficult to determine the prohibited zone by actual performance testing or operating records, the best economy is achieved by avoiding operation in areas that are in actual operation (Walters and Sheble, 1993; Yalcinoz and Short, 1998). Lee and Breipohl (1993) and Walters and Sheble (1993) showed the input-output performance curve for a typical thermal unit with many valve points. These valve points generate many prohibited zones. In practical operation, adjusting the generation output P_i of a unit must avoid unit operation in the prohibited zones. The feasible operating zone of unit i can be given as follows:

$$\begin{cases} P_i^{\min} \le P_i \le P_{i,1}^{\mathrm{l}}, \\ P_{i,k-1}^{\mathrm{u}} \le P_i \le P_{i,k}^{\mathrm{l}}, \\ P_{i,m_i}^{\mathrm{u}} \le P_i \le P_i^{\max}, \end{cases} \quad (5)$$

where k is the number of prohibited zones of unit i, and k=2, 3, ..., m_i.

(4) Generator operation constraints

$$\max(P_i^{\min}, P_i^0 - R_{\mathrm{d}i}) \le P_i \le \min(P_i^{\max}, P_i^0 + R_{\mathrm{u}i}), \quad (6)$$

$$P_i \in \begin{cases} P_i^{\min} \le P_i \le P_{i,1}^{\mathrm{l}}, \\ P_{i,k-1}^{\mathrm{u}} \le P_i \le P_{i,k}^{\mathrm{l}}, \\ P_{i,m_i}^{\mathrm{u}} \le P_i \le P_i^{\max}, \end{cases} \quad (7)$$

i=1, 2, ..., n; k=2, 3, ..., m_i.

(5) Line flow constraint

$$\left| P_{\mathrm{Lf},j} \right| \le P_{\mathrm{Lf},j}^{\max}, \ k = 1, \ ..., \ L, \quad (8)$$

where $F_i(P_i)$ is the generation cost function, n the number of generators committed to the operating system, P_i the power output of the ith generator, $P_{\mathrm{Lf},j}$ the real power flow of line j, L the number of transmission lines.

The total transmission network losses is a function of unit power outputs that can be represented using B coefficients (Gaing, 2003) by

$$P_{\mathrm{L}} = \sum_{i=1}^{n} \sum_{j=1}^{n} P_i B_{i,j} B_j + \sum B_{\mathrm{o}i} P_j + B_{\mathrm{oo}}. \quad (9)$$

Constraint satisfaction technique

To satisfy the equality constraint of Eq.(2), a loading of any one of the units is selected as the dependent loading P_{d} and its value is obtained from the following equation

$$P_{\mathrm{d}} = P_{\mathrm{D}} + P_{\mathrm{L}} - \sum_{i=1, i \ne d}^{n} P_i, \quad (10)$$

where P_{d} can be calculated directly from Eq.(10) with the known power demand P_{D} and the known values of remaining loading of the generators. Therefore the dispatch solution will always satisfy the power balance constraint provided that P_{d} also satisfies the operation limit constraint as given in Eqs.(6) and (7).

An infeasible solution is omitted and, the above procedure is repeated until P_d satisfies its operation limit. Because P_L also depends on P_d, we can substitute an expression for P_L in terms of $P_1, P_2, \ldots, P_d, \ldots, P_n$ and B coefficients. After substituting it into Eq.(10), the independent and dependent generator terms are separated to obtain a quadratic equation for P_d. Solving the quadratic equation for P_d, the power balance equality condition is exactly satisfied.

OVERVIEW OF PARTICLE SWARM OPTIMIZATION

The particle swarm optimization is one of the recent modern evolutionary algorithms which are suitable for solving highly nonlinear optimization problems. Researchers have presented a use of PSO for solving efficiently the ED problem, where PSO provides a population-based search procedure in which individuals called particles change their position (states) with time. In a PSO system particles fly around in a multi-dimensional search space. During flight, each particle adjusts its position according to its own experience and the experience of neighboring particles, making use of the best position encountered by it and its neighbors. The swarm direction of a particle is defined by the set of particles neighboring the particle and its history experience. Instead of using evolutionary operation to manipulate the individuals, like in other evolutionary computational algorithms, each individual in PSO flies in the search space with a velocity which is dynamically adjusted according to its own flying experience and its companions' flying experience.

Let X and V denote a particle coordinate (position) and its corresponding flight speed (velocity) in a search space respectively. Therefore, each ith particle is treated as a without-volume particle, represented as $X_i=(X_{i1}, X_{i2}, \ldots, X_{id})$ in the d-dimensional space. The best previous position of the ith particle is recorded and represented as $pbest_i=(pbest_{i1}, pbest_{i2}, \ldots, pbest_{id})$. The index of the best particle among all the particles is treated as global best particle, and is represented as $gbest_d$. The rate of velocity for particle 'i' is represented as $V_i=(V_{i1}, V_{i2}, \ldots, V_{id})$. The modified velocity and position of each particle can be calculated using the current velocity and the distance from $pbest_{id}$ to $gbest_d$ as shown in Eqs.(11) and (12):

$$V_{id}^{(t+1)} = \omega V_i^{(t)} + c_1 \cdot rand() \cdot (pbest_{id} - P_{\mathrm{g},id}^{(t)}) + c_2 \cdot Rand() \cdot (gbest_d - P_{\mathrm{g},id}^{(t)}), \quad (11)$$

$$X_{id}^{(t+1)} = X_{id}^{(t)} + V_{id}^{(t+1)}, \quad (12)$$

where i=1, 2, …, n; d=1, 2, …, m. n is the population size, m the number of units, ω the inertia weight factor, c_1 and c_2 acceleration constants, $rand()$ and $Rand()$ uniform random value in the range [0, 1], $V_i^{(t)}$ the velocity of particle 'i' at iteration 't', $V_{id}^{(t+1)}$ the (modified) velocity of particle 'i' at iteration 't+1', $V_{id}^{(t)}$ the velocity of particle 'i' at iteration 't', $X_{id}^{(t)}$ the current position of particle 'i' at iteration 't'.

In the above equations, c_1 has a range (1.5, 2), which is called self-confidence range; c_2 has a range (2, 2.5), which is called swarm range. The term $rand()\cdot(pbest_{id}-X_{id}^{(t)})$ is called particle memory influence and the term $Rand()\cdot(gbest_d-X_{id}^{(t)})$ is called swarm influence. $V_i^{(t)}$, the velocity of the ith particle at iteration 't', must lie in the range $[V_d^{\min}, V_d^{\max}]$. The parameter $V_d^{\max}$ determines the resolution, or fitness, with which regions are to be searched between the present position and the target position. If $V_d^{\max}$ is too high, particles may fly past good solutions. If $V_d^{\max}$ is too small, particles may not explore sufficiently beyond local solutions. In many experiences with PSO, $V_d^{\max}$ was often set at 10%~20% of the dynamic range on each dimension (Victoire and Jeyakumar, 2005).

The constants c_1 and c_2 pull each particle towards *pbest* and *gbest* positions. Low values allow particles to roam far from the target regions before being tugged back. On the other hand, high values result in abrupt movement towards, or past, target regions (Huang *et al*., 2005). Hence, the acceleration constants c_1 and c_2 are often set to be 2.0 according to past experiences. Suitable selection of inertia weight 'ω' provides a balance between global and local explorations, thus requiring less iteration on average to find a sufficiently optimal solution. As originally developed, ω often decreases linearly from about 0.9 to 0.4 during a run. In general, ω is set according to the following equation:

$$\omega = \omega_{\max} - \frac{\omega_{\max} - \omega_{\min}}{iter_{\max}} \cdot iter, \quad (13)$$

where ω is inertia weight factor, ω_{max} and ω_{min} maximum and minimum value of the weighting factor respectively, $iter_{max}$ the maximum number of iterations, $iter$ the current iteration number.

DEVELOPMENT OF PROPOSED HYBRID ALGORITHM

In this paper, the constrained ED problem is solved by the integrated GAPSO algorithm and a high quality solution is obtained within practical power system operation. The GAPSO algorithm is utilized to determine the optimal generation power of each unit that was submitted to operation at the specific period, thus minimizing the total generation cost. The following definitions are important before the application of the proposed algorithm for the ED solution.

Representation of individual string

In an efficient evolutionary method, the representation of chromosome strings of the problem parameter set is important. In this paper, the power output of each unit is taken as a gene, and many genes comprise an individual. Each individual within the population represents a candidate solution for the dispatch problem (Yang *et al*., 1996). For example, if there are n units that must be operated to meet a load, then the jth individual P_{gj} can be defined as follows:

$$P_{gj} = [P_{j1}, P_{j2}, P_{jd}],\ j = 1,\ 2,\ ...,\ n, \tag{14}$$

where n is the number of generating units, P_{jd} is the power output of dependent generating unit at the jth individual.

Evaluation function

The evaluation function f (called fitness in GA) must be defined for evaluating the fitness of each individual in the population. For emphasizing the best chromosome and faster convergence of the iteration process, the evaluation value is normalized in the range [0, 1]. f is given in Eq.(15) which is the reciprocal of the summation of generation cost function F_{cost} and power balance constraint P_{pbc} (Gaing, 2003):

$$f = 1/(F_{cost} + P_{pbc}), \tag{15}$$

where

$$F_{cost} = 1 + \text{abs}\left[\left(\sum F_i(P_i) - F_{min}\right)\Big/(F_{max} - F_{min})\right], \tag{16}$$

$$P_{pbc} = 1 + \left(\sum P_i - P_D - P_L\right)^2. \tag{17}$$

F_{max} and F_{min} are the maximum and minimum generation cost among the individuals in the initial population, respectively.

Proposed hybrid GAPSO algorithm

The sequential steps of the proposed hybrid GAPSO algorithm are given below.

Step 1: Initialize randomly the individuals of the population according to the limit of each unit including individual dimensions, searching points, and velocities. These initial individuals must be feasible candidate solutions that satisfy the operation constraints.

Step 2: To each chromosome of the population the dependent unit output P_d will be calculated from the power balance equation and B coefficient matrix.

Step 3: Calculate the evaluation value of each individual P_{gi}, in the population using the evaluation function f given by Eq.(15).

Step 4: Compare each individual's evaluation value with its *pbest*. The best evaluation value among the *pbest*'s is denoted as *gbest*.

Step 5: Modify the member velocity of each individual P_g according to Eqs.(11) and (12).

Step 6: Check the velocity components constraint occurring in the limits from the following conditions:

$$\left.\begin{array}{l}\text{If } V_{id}^{(t+1)} > V_d^{max}\text{, then } V_{id}^{(t+1)} = V_d^{max},\\ \text{If } V_{id}^{(t+1)} < V_d^{min}\text{, then } V_{id}^{(t+1)} = V_d^{min}.\end{array}\right\} \tag{18}$$

Step 7: Modify the member position of each individual P_g

$$P_{g,id}^{(t+1)} = P_{g,id}^{(t)} + V_{id}^{(t+1)}, \tag{19}$$

$P_{g,id}^{(t+1)}$ must be modified toward the near margin of the feasible solution.

Step 8: Apply the genetic operators selection, crossover and mutation to the above population and generate offspring. Now compare the parents and offspring to select the fittest chromosomes for the next step.

Step 9: If the evaluation value of each individual is better than previous *pbest*, the current value is set to *pbest*. If the best *pbest* is better than *gbest*, the value is set to be *gbest*.

Step 10: If the number of iterations reaches the maximum, then go to Step 11. Otherwise, go to Step 2.

Step 11: The individual that generates the latest *gbest* is the optimal generation power of each unit with the minimum total generation cost.

NUMERICAL EXAMPLES AND SIMULATION RESULTS

To verify the feasibility of the proposed hybrid algorithm, 15-unit and 40-unit power systems were taken and tested. The ramp rate limits and prohibited operating zones of the example problems are taken into account, so that the proposed hybrid GAPSO algorithm is compared with the GA method and PSO method. Each test system is subjected to 50 trials by the proposed algorithm to have a fair comparison with other methods in computation efficiency and solution quality. The software package in MATLAB was developed to solve the example problems by the proposed algorithm. The solutions by GA method and PSO method were directly taken from the source for comparison (Gaing, 2003), and the developed software package was executed on Pentium IV processor with 550 MHz CPU and 256 MB RAM.

The following parameters have been selected for the proposed hybrid GAPSO algorithm: population size=50; generations=100; inertia weight factor ω is set by Eq.(13), where $\omega_{\max}$=0.9 and $\omega_{\min}$=0.4; the limit of change in velocity of each member in an individual was as $V_d^{\max}=0.5P_{\mathrm{D,max}}$, $V_d^{\min}=-0.5P_{\mathrm{D,min}}$; acceleration constant c_1=2 and c_2=2; crossover probability=0.55; mutation probability=0.

Fifteen-unit system

This example problem contains 15 generating units, whose characteristics are obtained from (Lee and Breipohl, 1993). The total power demand of the system is 2 630 MW. The B loss coefficients are taken from (Lee and Breipohl, 1993). For this standard power system unit problem, each individual in the population contains 14 generator power outputs and the dimension of each population is 50×14. The simulation results and comparison of performance of all the methods are shown in Tables 1 and 2.

Table 1 Comparison of the best solution obtained by hybrid GAPSO with other methods

Parameter	Power output (MW)		
	GA	PSO	Hybrid GAPSO
P_1	415.3108	439.1162	436.8482
P_2	359.7206	407.9727	409.6974
P_3	104.4250	119.6324	117.0074
P_4	74.9853	129.9925	128.2705
P_5	380.2844	151.0681	153.3361
P_6	426.7902	459.9978	457.4078
P_7	341.3164	425.5601	424.4400
P_8	124.7867	98.5699	101.1949
P_9	133.1445	113.4936	116.1186
P_{10}	89.2567	101.1142	102.2243
P_{11}	60.0572	33.9116	35.0317
P_{12}	49.9998	79.9583	78.8482
P_{13}	38.7713	25.0042	27.1292
P_{14}	41.9425	41.4140	37.1594
P_{15}	22.6445	35.6140	37.0390
Total power output	2668.40	2662.40	2661.75
Power loss	38.40	32.40	31.75
Total generation cost ($/h)	33113	32858	32724

Table 2 Solution quality of the proposed hybrid algorithm

Method	Generation cost ($/h)			Average CPU time (s)
	Min.	Max.	Avg.	
GA	33113	33337	33228	49.31
PSO	32858	33331	33039	26.59
Hybrid GAPSO	32724	33188	32984	23.52

For a power demand of 2 630 MW, the total transmission losses are 31.75 MW for the optimal dispatch obtained by the proposed algorithm. As the total power output from all the 15 units is 2 661.75 MW, the power balance equation is exactly satisfied. The total generation cost as well as the power losses is less for the proposed algorithm compared with GA method and PSO method. Comparison of results obtained by various methods showed that the proposed algorithm can give optimal solution within a short execution time.

Fourty-unit system

The data for the 40-unit system were taken from (Chen and Chang, 1995), in which coal fired, oil fired, gas fired, diesel and combined cycle cogeneration units are present. The system load demand is 8550 MW. Since one unit is considered as a dependent unit, each individual in the population contains 39 generating units outputs. The dimension of the population is 50×39. The simulation results and comparison of performance are given in Tables 3 and 4.

Table 3 Comparison of the best solution obtained by hybrid GAPSO with other methods (40-unit system)

Parameter	GA	PSO	Hybrid GAPSO
Total power output (MW)	8641.08	8637.26	8636.58
Power loss (MW)	91.08	87.26	86.58
Total generation cost ($/h)	135070	130380	130255

Table 4 Solution quality of the proposed hybrid algorithm

Method	Generation cost ($/h)			Average CPU time (s)
	Min.	Max.	Avg.	
GA	135070	137980	137760	81.80
PSO	130380	137740	134970	59.45
Hybrid GAPSO	130255	136986	133678	52.39

Comparison of hybrid GAPSO, PSO and GA

1. Solution quality

The software package developed has been executed for 50 different runs for the proposed Hybrid GAPSO algorithm and the results are tabulated in Tables 1~4, which showed that the proposed hybrid GAPSO algorithm obtained lower average generation cost compared with the PSO method and GA method for all the three example problems. Fig.1 shows the plot of convergence of the best solution obtained by the proposed algorithm for 15-unit system. Comparison of results proved that the proposed algorithm has better quality of solution than the other methods.

2. Computation efficiency

Tables 1~4 showed that the proposed hybrid GAPSO has less average execution time compared with GA and PSO. Hence the computation efficiency of the proposed algorithm is proved. The above study showed that, even though execution time for one iteration is more because of the presence of GA operators, crossover and mutation, the identification of the high performance region and locating the optimal solution is possible within less number of iterations and hence the optimal solution was found within less average execution time.

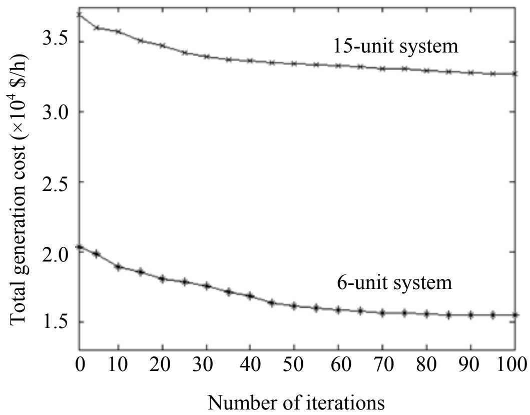

Fig.1 Convergence of the proposed algorithm (6-unit & 15-unit systems)

CONCLUSION

In this paper, the hybrid GAPSO algorithm has been successfully applied to solve the ED problem with generator constraints. The non-linear characteristics of the generator such as prohibited operating zones, ramp rate limits are considered for practical generator operation in the proposed algorithm and the constraint satisfaction technique has been successfully applied to generate feasible solutions. Comparison of results showed that the proposed algorithm can obtain higher quality of solution efficiently for ED problem.

In order to prove its superiority over other methods, many performance estimation measures such as "solution quality and convergence characteristics" and "computational efficiency" were performed and compared. The above study proved that the premature convergence characteristics of the GA method has been eliminated by integrating it with the PSO algorithm and that the proposed algorithm can give higher quality solution within a reasonable computation time.

ACKNOWLEDGEMENT

The authors are very thankful to the authorities of Pondicherry Engineering College and Sri Manakula Vinayagar Engineering College, Pondicherry, India for providing all the facilities to complete this work.

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