Optimization on Generation Expansion Planning by PSO and DP

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Abstract

This paper presents the objective of generation expansion planning is to aim at serving the demand at a specified level of reliability, at the lowest possible cost. The optimization techniques such as Dynamic Programming, Particle Swarm Optimization, are applied to solve GEP problem. The original GEP problem is modified using the proposed methods Virtual Mapping Procedure (VMP) and Penalty Factor Approach (PFA), to improve the efficiency of the techniques. Further, Intelligent Initial Population Generation (IIPG), is introduced in the solution techniques to reduce the computational time. The VMP, PFA, and IIPG are used in solving all the two test systems. The GEP problem considered synthetic test systems for 6-year and 14-year, planning horizon having five types of candidate units. The results obtained by these proposed methods are compared and validated against conventional Dynamic Programming and the effectiveness of each proposed methods has also been illustrated in detail.

Keywords

Generation Expansion Planning, Particle Swarm Optimization, Dynamic Programming, Virtual Mapping

I. Introduction

Generation Expansion Planning (GEP) is clear as the problem of determining which, where, and when new generation units should be constructed over a long range planning horizon, to gratify the expected energy demand. The GEP problem is considered difficult to solve for some reasons resulted from the vagueness associated with the input data, such as forecasts of demand for electricity, economic and technical characteristics of new developing generating technologies, construction lead times, and governmental regulations[1]. The generation expansion planning (GEP) problem seeks to make out which generating units should be custom-made and when they should become existing over the long-term planning horizon [1], [2]. This GEP model is valid for developing countries, where planning is matched by central or state government owned utilities for capacity addition. It is also applicable in a market-based industry for companies intending to serve load from multiple generation facilities [2]. The mean of a traditional power generation planning has been to give an enough supply of electrical energy at minimum cost, because non-linearity and complexity of GEP problem, a various approaches have been offered to solve and optimization that in traditional location. The main objectives of GEP are to minimize the sum investment and the operating cost of the generating units, and to meet the demand criteria, fuel-mix ratio, and the reliability criteria. Planning the expansion of electric systems is the high insecurity in fossil fuel prices and their rising trend. Despite the attractiveness of generation units that use gas to produce electricity, since they are cleaner and cheaper than the other fossil fuel technologies (oil and coal), the risks of high and undecided costs of this fuel type have to be considered in the planning process. The traditional approach is to formulate this problem as a single-objective optimization problem with constraints. This approach just results in a single optimal result where tradeoffs between different components of the objective function have to be fixed in advance of result. In this paper, the Particle Swarm optimization and Dynamic programming techniques are applied to solve the GEP problem. The GEP problem is also modified using Virtual Mapping Procedure (VMP), Penalty Factor Approach (PFA) and Intelligent Initial Population Generation (IIPG) approaches before solving for all two test systems using Optimization techniques. It is applied to a test system with 15 existing units, five types of candidate units for a planning period of 6-years, 14 years and the results obtained by all these proposed techniques are compared and validated.

II. GEP Problem Formulation

A. Objective Function

The GEP problem is equivalent to find a set of best decision vectors over a planning horizon that minimizes the investment and operating costs with several constraints. The cost function (objective function) is represented by the following expression:

\[
\min C = \sum_{i=1}^{N} [I(U_t) + M(X_t) + O(X_t) - S(U_t)]
\]

Where

\[
X_t = X_{t-1} + U_t; \quad (t=1,2,3\ldots\ldots T)
\]

\[
I(U_t) = (1+d)^{2t} \sum_{i=1}^{N} (C_{il} \times X_t^{il})
\]

\[
S(U_t) = (1+d)^{T-2t} \sum_{i=1}^{N} (C_{il} \times \delta_{t} \times U_t^{il})
\]

\[
M(X_t) = \sum_{i=1}^{N} \left( (1+d)^{1.5+t+s} \left( \sum (X_{t-i} \times FC) + MC \right) \right)
\]

\[
O(X_t) = OC \times \sum_{i=1}^{N} \left( (1+d)^{1.5+t+s} \right)
\]

\[
t' = 2(t-1), \quad T' = 2 \times T - t'
\]

\[
Ut = \sum_{i=1}^{N} (Ut^i)
\]

\[
Xt = \sum_{i=1}^{N} (Xt^i)
\]

Where

C. Total Cost (Rs);

\( U_t \): N-dimensional vector of newly introduced units in the stage (1stage=2years);

\( U_{t,i} \): No. of newly introduced units of type i in stage t;

\( X_{t,i} \): cumulative capacity vector of existing units in stage (MW);

\( X_{t,i} \): cumulative capacity of existing units of type in stage(MW);

\( I(U_t) \): present value of investment cost of the newly introduced unit at the t-th stage, (Rs);

\( M(X_t) \): present value of total operation and maintenance cost of existing and the newly Introduced units(Rs);

\( S(X_t) \): variable used to indicate that the maintenance cost is calculated at the middle of the each year

\( S(U_t) \): present value of the salvage value of the newly added unit
at t-th interval, (Rs);
\[ d \] discount rate;
\[ CI_i \] Capital investment cost of the i-th unit (Rs);
\[ \delta_i \] Salvage factor of i-th unit;
\[ T \] length of the planning horizon (in stages)
\[ N \] total number of different types of units
\[ FC \] fixed operation and maintenance cost of the units; Rs/MW
\[ MC \] variable operation and maintenance cost of the units (energy)
\[ Rs/MW; \]
\[ EENS \] expected energy not served, MWh;

B. Constraints

1. Upper Construction Limit
Let \( U_t \) be the units to be committed in the expansion plan at stage \( t \) that must satisfy the maximum construction capacity of the units to be committed:
\[ 0 \leq U_t \leq U_{\text{max},t} \]
(10)
Where \( U_{\text{max},t} \) is the maximum construction capacity of the units in stage \( t \).

Reserve margin : The selected units must satisfy the minimum and maximum reserve margin:
\[ (1+R_{\text{min}}) \times D_t \leq \sum_{i=1}^{N} X_{t,i} \leq (1+R_{\text{max}}) \times D_t \]
(11)
Where
\[ R_{\text{min}} \] minimum reserve margin
\[ R_{\text{max}} \] maximum reserve margin
\[ D_t \] demand at the t-th stage in MW;

2. Fuel Mix Ratio
The GEP has different types of generating units: for example coal, Liquefied Natural Gas (LNG), oil, and nuclear. The selected units along with the obtainable units of all types must satisfy the fuel mix ratio.

\[ \text{FM}_{j\text{min}} \leq \frac{X_{t,j}}{\sum_{i=1}^{N} X_{t,i}} \leq \text{FM}_{j\text{max}} \quad j=1, 2, 3 \ldots N \]
(12)
Where
\[ \text{FM}_{\text{min}} \] : minimum fuel mix ratio of jth type;
\[ \text{FM}_{\text{max}} \] : maximum fuel mix ratio of jth type
\( j \) : type of the unit (eg: oil, LNG, coal, nuclear)

4. Reliability Criterion
The selected units along with the existing units must satisfy a reliability criterion on loss of load probability (LOLP)
\[ \text{LOLP} \leq \varepsilon \]
(13)
Where \( \varepsilon \) is the reliability criterion for maximum allowable LOLP.

In addition, the energy produced by each unit and expected energy not served (EENS) is calculated using "equivalent energy function method". The EENS indices are used for outage cost calculation [2].

III. Implementation to GEP Problem
The inherent rule adhered by the members of birds and fishes in the swarm, enables them to move, synchronize, without colliding, resulting in an amazing choreography was the basic idea of PSO technique [7,8]. PSO is similar to EC techniques in which, a population of potential solutions to the problem under consideration is used to probe the search space. The major difference is that, the EC techniques use genetic operators whereas SI techniques use the physical movements of the individuals in the swarm.

A. Virtual Mapping Procedure (VMP)
To improve the effectiveness of the proposed approach, a novel mapping procedure called ‘virtual mapping procedure’ is used to solve the least-cost GEP problem. This mapping procedure transforms the number of candidate units for each year to a dummy variable (i.e.) it maps the yearly cumulative capacity numbers into one dummy variable. This dummy variable specifies the position of each agent in the swarm. The position is modified, by adding velocity with this dummy variable. This improves the performance of PSO.

The main advantage of using VMP for this GEP problem is to avoid the dimensionality problem since it handles single dummy variable. In addition, it needs less memory space.

Further, if the mapped variable took part in all the PSO related operation, a small change in the mapped variable will reduce the infeasible solutions.

The steps involved in VMP are as follows:
• Form all the possible combinations of the candidate units.
• Multiply the number of units with the corresponding capacities and adding them to get the total capacity.
• Arrange the total capacity in ascending order (see Table 1).

Thus, a multivariable could be mapped to a single variable problem.

To illustrate, this VMP could be explained with two numbers of 1000MW unit and two numbers of 700MW units, in Table 1. The capacities and the corresponding variables are arranged in ascending order, as shown in Table 2. If the dummy variable value is 4, it indicates one number of 1000MW and one number of 700MW units.

As five different types of units are assumed to be available for each stage, the array size will be increasing by the multiples of 5. However, when we use VMP, the decision variable obtained is a multiple of its number of stages; the array size becomes 3 for a 3-stage problem. Thus, a size reduction of 80% is realized and the same is evident from Table 2.

<table>
<thead>
<tr>
<th>X1 (1000MW)</th>
<th>X2 (700MW)</th>
<th>Total capacity (MW)</th>
<th>Y (dummy variable)</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>0</td>
<td>1</td>
<td>700</td>
<td>1</td>
</tr>
<tr>
<td>1</td>
<td>0</td>
<td>1000</td>
<td>2</td>
</tr>
<tr>
<td>0</td>
<td>2</td>
<td>1400</td>
<td>3</td>
</tr>
<tr>
<td>1</td>
<td>1</td>
<td>1700</td>
<td>4</td>
</tr>
<tr>
<td>2</td>
<td>0</td>
<td>2000</td>
<td>5</td>
</tr>
<tr>
<td>1</td>
<td>2</td>
<td>2400</td>
<td>6</td>
</tr>
<tr>
<td>2</td>
<td>1</td>
<td>2700</td>
<td>7</td>
</tr>
<tr>
<td>2</td>
<td>2</td>
<td>3400</td>
<td>8</td>
</tr>
</tbody>
</table>

Advantages of VMP:
(a) Reduces the array size of the problem for longer planning horizon. The size of the array will increase based on the linear multiple of the planning horizon. Thus, the dimensionality problem is avoided.
(b) Needs less memory space.
(c) Improves the Success Rate (SR), since the usage of metaheuristic operators (crossover, mutation, position updating) has its positive impact due to the application of VMP.
(d) IIPG (Table 3) becomes easier using this approach.
Table 2: Array Size Reduction With VMP

<table>
<thead>
<tr>
<th>Array Size</th>
<th>Planning Horizon</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>6-years (3-stages)</td>
</tr>
<tr>
<td>Original</td>
<td>15</td>
</tr>
<tr>
<td>VMP</td>
<td>3</td>
</tr>
<tr>
<td>Size reduction in (%)</td>
<td>80%</td>
</tr>
</tbody>
</table>

B. Intelligent Initial Population Generation (IIPG)
The convergence of the techniques depends mainly on the selection of initial population. The use of reserve margin criterion narrows down the search space by creating a tunnel. The solution space is further restricted by IIPG, by considering the minimum and maximum cumulative capacity assumed to be available in the previous stages. This is also common for all the metaheuristic techniques. Table 3. shows the required capacities of 3-stage, 6-year planning horizon. In stage I, if the total capacity including the existing capacity is 8400 MW, then the maximum capacity required in stage II will be 4200 MW. Similarly, if the total capacity is 9800 MW, then the minimum capacity required in stage II will be 1000 MW.

Table 3: Intelligent Initial Population Generation

<table>
<thead>
<tr>
<th>Stages</th>
<th>I (in MW)</th>
<th>II (in MW)</th>
<th>III(in MW)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Demand</td>
<td>7000</td>
<td>9000</td>
<td>10000</td>
</tr>
<tr>
<td>Min demand D×(1+R_{max})</td>
<td>8400</td>
<td>10800</td>
<td>12000</td>
</tr>
<tr>
<td>Max demand D×(1+R_{max})</td>
<td>9800</td>
<td>12600</td>
<td>14000</td>
</tr>
<tr>
<td>Min capacity (8400-5450*)</td>
<td>2950</td>
<td>(10800-9800)</td>
<td>0</td>
</tr>
<tr>
<td>Max capacity (9800-5450)</td>
<td>4350</td>
<td>(12600-8400)</td>
<td>(14000-10800)=3800</td>
</tr>
</tbody>
</table>

*Existing Capacity

D. Implementation Using Individual Techniques

A. Particle Swarm Optimization
PSO can be defined as an iterated search procedure, which will guide the heuristics by combining different concepts for exploring and exploiting the solutions in the search space. Before solving the GEP problem it is modified and various techniques are applied. The detailed modifications are as follows:

B. Initialization of Agents and Their Velocity in the Swarms
The initial agents are selected randomly from the mapped variable. The velocities of each agent are also selected randomly between 0 and 1. The size of the swarm will be (Np × n), where Np is the total number of agents in the swarm and ‘n’ is the number of stages.

Here, 2 years planning period is assumed as one stage.

C. Updating the Velocity
The velocity is updated by considering the current velocity of the agent, the best fitness function value of that agent, and the best fitness function value among the agents in the swarm. The velocity of each agent is modified by (13). The value of the weighting factor ‘w’ in (13) is decremented by (15) to enable quicker convergence.

V^{k+1}_i = w × V^k_i + C_1 × rand_i × (Pbest^k_i - x^k_i) + C_2 × rand_i × (Gbest^k_i - x^k_i)

D. Updating the Position
The position of each agent is updated by adding the updated velocity with the current position of the individual in the swarm. The position of the ith individual at (k + 1)th iteration is found by (14).

E. Fitness Function Evaluation (Penalty Function Approach)
The fitness function of the agents is evaluated using (1). As the individuals are selected randomly, there is a possibility of obtaining infeasible solution. The infeasible solutions are avoided in the subsequent iterations by using PFA. In this approach, the objective function is evaluated and the reserve margin, LOLP and fuel mix ratio are checked for constraint violation. If the constraints are violated, then proportional penalty value is added to the objective function.

The objective function with penalty function approach is given as fitness function cost (FC):

FC = [C_i + \alpha_1 \sum \psi_2 + \alpha_2 \sum \psi_3 + \alpha_3 \psi_4] (16)

where FC is the fitness function value of ith individual, C_i the objective function value of ith individual, \alpha_1 the penalty factor for the constraint, reserve margin, \psi_2, the violation amount of the constraint, reserve margin, \alpha_2 the penalty factor for the constraint, fuel mix ratio, \psi_3, the violation amount of the constraint, fuel mix ratio, \alpha_3 the penalty factor for the constraint LOLP and \psi_4 is the violation amount of the constraint, LOLP.

Best Parameters

<table>
<thead>
<tr>
<th>Methods (Parameters)</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>PSO</td>
<td></td>
</tr>
<tr>
<td>Population size : 50</td>
<td></td>
</tr>
<tr>
<td>Max no. of iterations = 200</td>
<td></td>
</tr>
<tr>
<td>W_{max} = 1.2</td>
<td></td>
</tr>
<tr>
<td>W_{max} = 0.2</td>
<td></td>
</tr>
<tr>
<td>C_1 = 2.0</td>
<td></td>
</tr>
<tr>
<td>C_2 = 2.0</td>
<td></td>
</tr>
</tbody>
</table>

E. Dynamic Programming
The Dynamic Programming (DP) is the most robust and detailed capacity optimization technique of the present times. Though, its major shortcoming is the large amount of computation required to analyze, its search-space is, however comprehensive and facilitates enumeration of all possible, planning alternative in each year of the planning period by selecting minimum cost transitions from
one year to the next. The basic problem of optimization concerning expansion planning in electric power systems can be formulated as follows: In each year, there are many combinations of alternative resources that constitute the feasible state variables. For example, in the first year there may be three possible states, namely, addition of one 1000 MW purchased power, addition of one 400 MW coal-fired unit, or add three 100 MW gas turbines to the existing system. As the year progresses, the number of states may increase due to more capacities are needed to meet the new demand; also there are many other combinations of different types of alternative resources may emerge which can meet the present requirements. This usually leads to the “curse of dimensionality”, because the computational search-space increases with the number of states monotonically; and the number of state variables themselves would increase exponentially with the number of alternative types of units incorporated.

Therefore, without some constraints or limitations on the number of states, it is rather impractical to solve the problem even with more than four or five alternative for 10 to 20 years planning period. Hence, developed in the present theory, an optimization algorithm using the constraints described previously to arrive at least four alternative expansion plans simultaneously. The additional concept introduced to improve the effectiveness of the proposed techniques is VMP and PFA.

**IV. Test Results**
The PSO and D.P technique for GEP problem was implemented using MATLAB on a PC with Pentium 500MHz processor.

**A. Test System Description**
The PSO and D.P techniques and DP have been applied to test systems having 6-year, 14-year planning horizon with five types of candidate units. The forecasted load demand is given in Table 4. The technical data for the existing units and candidate units are taken from [3]. The test system consists of 15 existing units and five different fuel types of new candidate units, with the maximum construction capacity of 5, 4, 3, 3, and 3 are assumed to be present in every stage as shown in Table 5 and Table 6. Three test cases are considered.

<table>
<thead>
<tr>
<th>Years</th>
<th>Demand (MW)</th>
</tr>
</thead>
<tbody>
<tr>
<td>2012</td>
<td>5000</td>
</tr>
<tr>
<td>2014</td>
<td>7000</td>
</tr>
<tr>
<td>2016</td>
<td>9000</td>
</tr>
<tr>
<td>2018</td>
<td>10000</td>
</tr>
<tr>
<td>2020</td>
<td>12000</td>
</tr>
<tr>
<td>2022</td>
<td>13000</td>
</tr>
<tr>
<td>2024</td>
<td>14000</td>
</tr>
<tr>
<td>2026</td>
<td>15000</td>
</tr>
</tbody>
</table>

**Table 5: Economic and technical data of existing plants are provided in Table 2 and candidate plant types for future additions is given in Table 3.**

<table>
<thead>
<tr>
<th>Name (fuel Type)</th>
<th>No. Of units</th>
<th>Unit capacity (MW)</th>
<th>Operating Cost (Rs/KWh)</th>
<th>Fixed O&amp;M Cost ($/KW-Month)</th>
<th>Capital Cost (Rs/MW)</th>
<th>Life Time (Yrs)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Oil#1 (heavy oil)</td>
<td>1</td>
<td>200</td>
<td>7.0</td>
<td>0.024</td>
<td>2.25</td>
<td></td>
</tr>
<tr>
<td>Oil#2 (heavy oil)</td>
<td>1</td>
<td>200</td>
<td>6.8</td>
<td>0.027</td>
<td>2.25</td>
<td></td>
</tr>
<tr>
<td>Oil#3 (heavy oil)</td>
<td>1</td>
<td>150</td>
<td>6.0</td>
<td>0.030</td>
<td>2.13</td>
<td></td>
</tr>
<tr>
<td>LNG G/T#1 (LNG)</td>
<td>3</td>
<td>50</td>
<td>3.0</td>
<td>0.043</td>
<td>4.52</td>
<td></td>
</tr>
<tr>
<td>LNG C/C#1 (LNG)</td>
<td>1</td>
<td>400</td>
<td>10.0</td>
<td>0.038</td>
<td>1.63</td>
<td></td>
</tr>
<tr>
<td>LNG C/C#2 (LNG)</td>
<td>1</td>
<td>400</td>
<td>10.0</td>
<td>0.040</td>
<td>1.63</td>
<td></td>
</tr>
<tr>
<td>LNG C/C#3 (LNG)</td>
<td>1</td>
<td>450</td>
<td>11.0</td>
<td>0.035</td>
<td>2.00</td>
<td></td>
</tr>
<tr>
<td>Coal#1 (Anther cite)</td>
<td>2</td>
<td>250</td>
<td>15.0</td>
<td>0.023</td>
<td>6.65</td>
<td></td>
</tr>
<tr>
<td>Coal (Bituminous)</td>
<td>1</td>
<td>500</td>
<td>9.0</td>
<td>0.019</td>
<td>2.81</td>
<td></td>
</tr>
<tr>
<td>Coal#3 (Bituminous)</td>
<td>1</td>
<td>500</td>
<td>8.5</td>
<td>0.015</td>
<td>2.81</td>
<td></td>
</tr>
<tr>
<td>Nuclear #1 (PWR)</td>
<td>1</td>
<td>1000</td>
<td>9.0</td>
<td>0.005</td>
<td>4.94</td>
<td></td>
</tr>
<tr>
<td>Nuclear#2 (PWR)</td>
<td>1</td>
<td>1000</td>
<td>8.8</td>
<td>0.005</td>
<td>4.63</td>
<td></td>
</tr>
</tbody>
</table>

The second column in Table 3 denotes an upper limit on the number of units of each candidate option per stage which reflects the construction capabilities by plant type. The last column in Table 3 is associated with the evaluation of salvage value of a plant that operates beyond the planning horizon.

The lower and upper bounds for reserve margin are set at 20% and 40% respectively. The salvage factor is assumed to be 0.1, 0.15, 0.2 and 0.2 for oil, LNG, Coal, PWR and PHWR respectively. The discount rate is 8.5%. It is assumed the first possible availability date of new generation is two years beyond the current date. The year investment cost is assumed to occur in the beginning of year. The year maintenance cost is assumed to occur in the middle of the year and is calculated by the equivalent energy function method. The year salvage cost is assumed to occur
B. Parameters for GEP

The parameters pertaining to the GEP problem are taken from [6]. Practically, the lower and upper bounds for reserve margin are set to 20 and 40% to meet any failure in generating units and to carry out maintenance activities. The salvage factor is additionally added to include the depreciation value of the units in calculating the salvage value of the newly added units. Additionally the following parameters are assumed and used in solving the GEP problem. The unserved energy (EENS) cost is set at 0.05 Rs./kWh. The initial period is 2 years. The investment cost, maintenance cost, and salvage cost are assumed to occur at the beginning of the year, middle of the year, and at the end of the planning period, respectively. The outage cost is determined using the EENS indices.

The lower and upper bounds for reserve margin are set at 20% and 40% respectively. The salvage factor is assumed to be 0.1, 0.1, 0.15, 0.2 and 0.2 for oil, LNG, coal, PWR, and PHWR, respectively. The discount rate is 8.5%. It is assumed the first possible availability date of new generation is two years beyond the current date. The year investment cost is assumed to occur in the beginning of year; the year maintenance cost is assumed to occur in the middle of year and is calculated by the equivalent energy function method [2]. The year salvage cost is assumed to occur at the end of the planning horizon.

C. Impact of PFA

The most important aspect of dealing with constrained optimization problem is how to handle constraints, since the offspring obtained from the selected parents, will be, often infeasible offspring. Several techniques have been proposed to handle constraints to solve constrained optimization problems.

The most common technique used to handle infeasible solution is the PFA. This technique transforms the constrained problem into an unconstrained problem, in which a penalty term is added with objective function value on any violation of the constraints. To study the effectiveness of PFA, experiments have been conducted without PFA. A random population of 500 was generated. Similarly, ten simulations run were taken. From Table 6, it is evident that, without PFA, the SR of generation of feasible solution is only 0.004% (i.e.2/500). The experimentation is carried out for 6-year planning horizon to study the effectiveness of VMP, PFA and IIPG. The population size is set as 50 and maximum generation is set as 500. The tests are conducted for 50 simulation runs.

D. Impact of IIPG and VMP

The IIPG approach is used to limit the search space based on the reserve rate criterion. The total capacities available are between 0MW and 9400MW. The total existing capacity is 5450 MW. The minimum and maximum demand for the first stage will be 8400 to 9800 MW. The minimum amount of capacity required to satisfy the minimum demand criterion will be 2950 MW and the maximum capacity required to satisfy the maximum demand criterion will be 4350 MW. Instead of taking all the capacities between 0 to 9400MW, the IIPG took only the capacities between 2950 to 4350 MW. Thus the solution space is reduced. This IIPG is used in conjunction with VMP. In VMP, the capacities are arranged in the ascending order and the mapped variables are arranged continuously based on the capacities.

E. Test System-2: 14-Year Planning Horizon

The experiments were conducted for the 14-planning horizon, (with VMP, with IIPG and with PFA) and the results are summarized respectively. The simulations were carried out for 25 runs. Since the techniques do not converge to the optimal solution for
the best parameters of 6-year planning horizon, tests are also conducted for other parameters. Even then, it is observed that there are no signs of converging to the best solution.

Table 9: Results Obtained for 14-Year Planning Horizon

<table>
<thead>
<tr>
<th>Stages (MW)</th>
<th>D.P Cost(Rs)</th>
<th>Execution Time (Sec)</th>
</tr>
</thead>
<tbody>
<tr>
<td>12000</td>
<td>$1.795 \times 10^{10}$</td>
<td>200</td>
</tr>
<tr>
<td>13000</td>
<td>$2.0043 \times 10^{10}$</td>
<td>855.5</td>
</tr>
<tr>
<td>14000</td>
<td>$2.0043 \times 10^{10}$</td>
<td>525</td>
</tr>
<tr>
<td>15000</td>
<td>$2.1797 \times 10^{10}$</td>
<td>22 mins</td>
</tr>
</tbody>
</table>

PSO Results for 14-year planning horizon

<table>
<thead>
<tr>
<th>Best cost (Rs)</th>
<th>Worst Cost (Rs)</th>
<th>Error (%)</th>
<th>Exe. Time (sec)</th>
</tr>
</thead>
<tbody>
<tr>
<td>$2.0346 \times 10^{10}$</td>
<td>$2.1109 \times 10^{10}$</td>
<td>0</td>
<td>46.431</td>
</tr>
</tbody>
</table>

Fig. 3: Convergence Characteristics of D.P in 14 Years Planning Horizon

In general, it is found that the PFA helps in producing feasible solutions and their success rate is improved with IIPG. However if IIPG is used in conjunction with VMP the success rate is found to be high.

Fig. 4: Convergence Characteristics of PSO in 14 Years Planning Horizon

V. Conclusion

The “2” techniques PSO and D.P were applied for three test cases to solve the least-cost GEP problem. Their performances were compared in terms of their success rate and execution time. The efficiency of the techniques was improved by the application of virtual mapping procedure, intelligent initial population generation, and penalty factor approach. The drawbacks of DP were overcome by the modified techniques. The optimal or near optimal solution was obtained within a reasonable time. The proposed modifications in these techniques increased the success rate. Among the techniques, the hybrid approach performed better, and avoided trapping in local minima even for larger dimension problems.

References