APPLICATION OF BACTERIA FORAGING STRATEGY FOR SHORT TERM HYDRO THERMAL SCHEDULING PROBLEM

Mariappane Egambaram
Dr.Pauls Engineering College,
Vanur Taluk, Villupuram Dt,
Tamilnadu, India.
dev_mari@rediffmail.com

Dr. Thyagarajah Kuppusamy
K.S.Rangasamy College of Technology,
nammakal Dt, Thiruchengode,
Tamilnadu, India.

Dr. Sudhakaran Mahalingam
Pondicherry Engineering College,
Pillaichavadi,
Pondicherry, India.

ABSTRACT
Optimization is an important term without which the field of engineering will not be existing. Power engineers will take many technical assessments at several stages of the power system operation. The ultimate objective of all such assessments is to either maximize the desired gain or to minimize the sweat or the cost required. This paper presents a new, bacteria foraging algorithm for solving the short-term hydro thermal scheduling problem. The proposed method is developed in such a way that a bacteria foraging strategy is acting as a base level search, which makes a quick decision to direct the search towards the optimal region and local searches are next employed to fine tune the search to reach the exact optimal solution. In order to validate the effectiveness of the proposed bacteria foraging algorithm in solving short-term hydrothermal scheduling problem, results were obtained for a test system with a hydro plant and an equivalent thermal plant for a time schedule of six 12-hour intervals. The results obtained by the proposed method are compared with other methods and they undoubtedly demonstrate that the proposed method is practical and valid for real time applications.

KEY WORDS
Hydrothermal scheduling, Bacteria foraging strategy, Local Search, Combinatorial optimization, Chemotaxis, Swimming.

1. Introduction

The short term hydrothermal scheduling problem is dealt with assigning generation among hydro units and thermal units over little period of time, usually discretized in hourly intervals. It is the process of finding generation among the hydroelectric and thermal plants so as to minimize total operation cost of thermal plants while satisfying the various constraints on the hydraulic and power system network. The constraints related to the short term hydrothermal scheduling consist of load balance, operating capacity limits of the hydro and thermal units, water discharge rate, upper and lower bounds on reservoir volume, water spillage and hydraulic continuity restrictions. Many more constraints can be imposed depending on the particular requirements of a given power system, such as the need to satisfy activities including flood control, irrigation, fishing, water supply etc. The conventional methods available for solving the hydrothermal scheduling problem make a number of simplifying assumptions in order to make the search process more efficient [1], [2].

For the solution of the hydrothermal scheduling problem, several methods have been available in the literature such as nonlinear programming, branch and bound, dynamic programming, network flow algorithms, Newton’s method, expert systems, artificial neural network, genetic algorithms and evolutionary programming [2]. If the cost equations of example systems are in differentiable form, the above methods will give optimum results. If the cost functions are not in a differentiable form, then above methods will give only local optimal solutions. The dynamic programming method is a very popular method among the conventional methods. However, a major disadvantage of the DP method is that the computational and dimension requirements grow drastically with increasing system size. The biology based evolutionary algorithms are genetic algorithms (GAs), evolutionary programming (EP), evolutionary strategy (ES), genetic programming (GP) and bacteria foraging algorithm (BFA) [3], [4]. Among the above algorithms, the bacteria foraging algorithm is having number of advantages over conventional optimization techniques [5], [6], [7]. The algorithmic structure of the bacteria foraging algorithm is very simple and they have the ability to handle all the linear and nonlinear constraints very efficiently with less computation time. Paasino et all have introduced the Bacterial Foraging Algorithm (BFA) who models the foraging behavior of Escherichia coli bacteria present in our intestines [8]. The concept behind the BF algorithm is based on the fact that natural selection tends to eliminate animals with poor foraging strategies and favor those having successful foraging strategies [5]. Even though, the proposed algorithm has superior search ability, it fails to meet the high expectation of getting a qualitative solution at the end of search process. As widely accepted that bacteria foraging strategy is able to identify the more promising region of the solution space at an affordable time and display inherent difficulties in performing local search for numerical applications [5].
Passino suggested that the BFA should be used to perform the initial search to reach the more promising region, once the high performance regions of the search space are identified by a BFA, the local search methods should be employed to locate the global optimal solution[8].

In the proposed method, a bacteria foraging algorithm is applied to drive search process towards the promising region. Then local searches are incorporated to locate the optimal solution at quick execution time.

2. Problem Formulation

The hydrothermal scheduling problem is a power system optimization problem with an objective function, which is a concatenation of linear, non-linear and dynamic network flow constraint [4], [9]. Since the hydro generating units have zero incremental cost, the hydrothermal scheduling problem is aspired to optimize the system thermal cost, while trying to maximize the hydro electric power generation. The objective function and associated constraints of the hydrothermal scheduling problem are formulated as follows:

2.1 Objective Function

The objective function of the hydrothermal scheduling problem is the minimization of the thermal power generation cost [4], [9], [10].

\[
F_{CTK} = \sum_{t=1}^{T} \sum_{i=1}^{n} FC_i(P_{ai}(t))
\]  

(1)

2.2 Constraints

(i) Power balance equation

\[
D_t = \sum_{i=1}^{n} P_{ai}(t) + \sum_{j=1}^{m} P_{hyj}(t) - P_L
\]  

(2)

The hydro generation \( P_{hyj} (t) \) is a function of water discharge rate and storage volume.

(ii) Thermal generation capacity

\[
P_{stimin} \leq P_{ai}(t) \leq P_{stimax}
\]  

(3)

(iii) Hydro generation capacity

\[
P_{hyjmin} \leq P_{hyj}(t) \leq P_{hyjmax}
\]  

(4)

(iv) Hydraulic Continuity

\[
V_j(t+1) = V_j(t) + q_j(t-m) + s_j(t-m) - q_h(t) - s_j(t) + r_j(t)
\]  

(5)

Where \( m \) is the water delay time between reservoir \( j \) and its upstream \( l \) at interval \( t \).

(v) Initial and final reservoir storage

\[
V_j(0) = V_0; V_j(T) = V_T
\]  

(6)

Reservoir storage

\[
V_{jmin} \leq V_j(t) \leq V_{jmax}
\]  

(7)

(vi) Water discharge rate

\[
q_{jmin} \leq q_j(t) \leq q_{jmax}
\]  

(8)

(vii) Total water discharge

\[
q_{jtot} = \sum_{t=1}^{T} q_{j}(t)
\]  

(9)

where

\[
D_t : \text{System load demand at interval } t
\]  

\[
FC_i(\ast) : \text{Fuel cost function of the } i^{th} \text{ thermal unit}
\]  

\[
F_{CTK} : \text{Objective function value of } k^{th} \text{ individual of a population}
\]  

\[
n : \text{Number of thermal generating units}
\]  

\[
m : \text{Number of hydro generating units}
\]  

\[
P_{ai}(t) : \text{Thermal generation of unit } i \text{ at interval } t
\]  

\[
P_{hyj}(t) : \text{Hydro generation of plant } j \text{ at interval } t
\]  

\[
P_L : \text{Total Transmission loss}
\]  

\[
P_{hyjmin}, P_{hyjmax} : \text{Minimum and maximum generation capacity limits of thermal unit}
\]  

\[
P_{hyjmin}, P_{hyjmax} : \text{Minimum and maximum generation capacity limits of hydro unit}
\]  

\[
q_j(t) : \text{Water discharge rate of plant } j \text{ at interval } t
\]  

\[
r_j(t) : \text{Inflow rate into the storage reservoir of plant } j \text{ at interval } t
\]  

\[
s_j(t) : \text{Spillage of reservoir } j \text{ at interval } t
\]  

\[
T : \text{Number of hours in the study period}
\]  

\[
V_j(t) : \text{Reservoir storage volume of plant } j \text{ at interval } t
\]  

\[
V_0, V_T : \text{Initial and final reservoir storage}
\]

3. Bacteria Foraging Strategy

The bacteria foraging algorithm employs the natural selection of universal optimum bacterium which has the successful foraging strategies as the cost function [5]. The proposed algorithm easily handles all the constraints associated with the hydro thermal scheduling. BFA is one of the successful robust algorithms for the solution of nonlinear optimization problems. The algorithm has the capability of completing the search at a less computation time and able to find the near global optimal solution [11], [12]. The algorithmic steps of the proposed method is formulated as a flow chart and is shown in figure 1.

3.1 Important operators of Bacteria foraging strategy

3.1.1 Chemotaxis

The process of chemotaxis is completed by two processes called swimming and tumbling. The rotary motion of the flagella in every bacterium decides whether it should move in a predefined route (swimming) or an altogether different route (tumbling), in the entire life span of the bacterium. The process of swimming and tumbling are decided by rotary motion of the flagella in each bacterium. To characterize a tumble, a unit length random direction, \( \phi (j) \) say, is generated; this will be utilized to define the direction of movement after a tumble [5].
3.1.3 Reproduction

The least healthy bacteria die, and other strong bacteria each split into two bacteria. These are placed in same location which makes the population of bacteria constant. There by, saturation of bacteria is eliminated [5], [8].

3.1.4 Elimination and dispersal

The span of life of bacteria changes either slowly or suddenly on the basis of consumption of nutrients or due to some other external factors. Some events happen in the environment can either kill or disintegrate all the bacteria in a environment[5]. They have the effect of possibly destroying the chemotactic progress, but in contrast, they also assist it, since dispersal may place bacteria near good sources[7], [8]. The processes elimination and dispersal helps in premature saturation of bacteria in local optimal points.

3.1.5 Local Searches

In every iteration, two local search processes 1-opt and 2-opt, were applied to the best solution of the new generation. The first process 1-opt spins one bit of the solution matrix, whereas the second process 2-opt switches the status of two bits at a time. The second operator first explores for improvement by flipping the status of two bits at each chromosome[2]. Then, the search prolongs by switching the status of a bit at two different chromosomes. As soon as a superior solution is found the local search is stopped and the modified solution replaces the original solution in the new generation [2].

4. Algorithmic Steps of Bacteria Foraging Algorithm

The main aim of genetic simulation is to provide a feasible solution in the population pool of each generation and achieve the objective of minimization through these feasible solutions in further evolutions [5].

Step 1: Initialization
• The following variables are initialized
  o Number of bacteria (S) used in the Search
  o Number of parameters (p) to be optimized
  o Swimming length Ns
  o Number of iterations in a chemotactic Loop Nc
  o The number of reproductions Nrep
  o Number of elimination & dispersal events Ned
  o Probability of elimination and dispersal Ped
  o Location of each bacterium
  o d attracts, θ attract, h repelent, θ repelent and are fixed values

Step 2: Iterative algorithm for optimization
• This section models the bacterium population chemotaxis, swarming, reproduction, and elimination and dispersal [5].
  o Elimination-dispersal loop : l = l + 1
  o Reproduction loop : k = k + 1
  o Chemotaxis loop : j = j + 1

Step 3: Chemotaxis loop
• For i =1,2,…,S calculate the cost function value for each bacterium.
  o Location of the bacterium corresponding to global minimum cost function.
  

\[ J_{sw}(i, j, k, l) = J(i, j, k, l) + J_{cc} \left( \theta^i(j, k, l), P_{attr}(j, k, l) \right) \]
  
  o Let \( J_{last} = J_{sw}(i, j, k, l) \) to save this value since we may find a better value
  o End of for loop

• For i =1,2,…,S take the tumbling/swimming decision
  o Tumble :
    • Generate random vector
      \[ \theta^i(j + 1, k, l) = \theta^i(j, k, l) + c(i) \frac{\Delta(i)}{\sqrt{\Delta(i)^2 + \Delta(i)}} \]
      • Compute cost function
Swim:
- Let \( m = 0 \)
- While \( m < N_s \)
  - Let \( m = m + 1 \)
  - If \( J_{sw}(i, j + 1, k, l) < J_{last} \)
    then \( J_{last} = J_{sw}(i, j + 1, k, l) \)
  - Else \( m = N_s \)
- Go to next bacterium (i+1) if \( i \neq S \) to process the next bacterium
- If \( j > N_c \), go to step 3. In this case, continue chemotaxis since life of bacteria is not over.

Step 4: Reproduction
- For a given \( k \) and \( l \), and for each \( i = 1, 2, ..S \), let \( J_{i, \text{health}} \) be the health of the bacterium \( i \).
- \( J_{i, \text{health}} \) is the minimum of \( J_{sw} \)
- The \( S_r = S/2 \) bacteria with highest \( J_{i, \text{health}} \) dies and other \( S_r \) bacteria with best value split into two.
- If \( k < N_{re} \), go to step 2; i.e. the Chemotactic loop.

Step 5: Elimination and dispersal
- For \( i = 1, 2, .., S \), with probability \( P_{ed} \) eliminates and disperses each bacterium. To do this, if one eliminates a bacterium, simply dispere it to a random location on the optimization domain [5].

Evaluation of the objective function is carried out and the process is repeated till no further improvement in the objective can be obtained [13], [14].

5. Test Case and Simulation Results

The test system with one hydro generating unit and one thermal unit has been taken for the study and the proposed algorithm is applied to solve the problem. The example system is taken from Yang et al [11].

It consists of a hydro plant and an equivalent thermal plant. The load patterns over six 12-hour intervals are shown in table 1.

<table>
<thead>
<tr>
<th>Interval Number</th>
<th>Day</th>
<th>Interval</th>
<th>Demand (MW)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>1\textsuperscript{st} day</td>
<td>0 hour – 12.0 hour</td>
<td>1200</td>
</tr>
<tr>
<td>2</td>
<td>1\textsuperscript{st} day</td>
<td>12.0 hour – 24.0 hour</td>
<td>1500</td>
</tr>
<tr>
<td>3</td>
<td>2\textsuperscript{nd} day</td>
<td>0 hour – 12.0 hour</td>
<td>1100</td>
</tr>
<tr>
<td>4</td>
<td>2\textsuperscript{nd} day</td>
<td>12.0 hour – 24.0 hour</td>
<td>1800</td>
</tr>
<tr>
<td>5</td>
<td>3\textsuperscript{rd} day</td>
<td>0 hour – 12.0 hour</td>
<td>950</td>
</tr>
<tr>
<td>6</td>
<td>3\textsuperscript{rd} day</td>
<td>12.0 hour – 24.0 hour</td>
<td>1300</td>
</tr>
</tbody>
</table>

The fuel cost function in dollars per hour of the equivalent thermal plant is as follows:

\[
F(P_d) = 0.00184 P_d^2 + 9.20 P_d + 575 ;
\]

\(150 \leq P_d \leq 1500\)

The hydro power generation relationship to water discharge is denoted as:

\[
q = 4.97 P_{hy} + 330 ; \quad 0 \leq P_{hy} \leq 1000
\]

\[
q = 0.05 (P_{hy} - 1000)^2 + 12 (P_{hy} - 1000) + 5300 ; \quad 1000 \leq P_{hy} \leq 1100
\]

The data for the hydro plant is given in table 2.

<table>
<thead>
<tr>
<th>( V_{\text{min}} ) (m(^3))</th>
<th>( V_{\text{max}} ) (m(^3))</th>
<th>( q_{\text{min}} ) (m(^3)/hr)</th>
<th>( q_{\text{max}} ) (m(^3)/hr)</th>
<th>( V_0 ) (m(^3))</th>
<th>( V_6 ) (m(^3))</th>
<th>( R ) (m(^3)/hr)</th>
</tr>
</thead>
<tbody>
<tr>
<td>60000</td>
<td>120000</td>
<td>330</td>
<td>7000</td>
<td>100000</td>
<td>60000</td>
<td>2000</td>
</tr>
</tbody>
</table>

The following control parameters have been chosen after running a number of simulations [5]:

The parameters used in BFA are as follows:

Number of Bacteria - 40
Number of iteration in Chemotactic Loop - 6.
Swimming Length - 4
Number of Reproduction - 2
Probability of elimination and dispersal - 0.25
\( d_{\text{attract}} \) - 0.25
\( \omega_{\text{attract}} \) - 3e\(^{-6}\)
\( h_{\text{repelent}} \) - 0.25
\( \omega_{\text{repelent}} \) - 15e\(^{-5}\).

The example problem was solved by the by proposed algorithm and the result is compared with the other methods like gradient search, simulated annealing, genetic algorithm, evolutionary programming (EP) method and hybrid EP method.
All the programs were developed using MATLAB programming and the example problem was run for 50 independent trials. In order to compare the efficiency of different algorithms, the results of gradient search, simulated annealing and GA were directly taken from Yang et al [11] and results of EP and hybrid EP were taken from S Baskar et al [13].

### Table 3
Comparison of results from Different Algorithms

<table>
<thead>
<tr>
<th>Sl. No</th>
<th>Optimization Method</th>
<th>Generation Cost ($)</th>
<th>CPU Time (Sec)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Gradient Search [7]</td>
<td>709877.38</td>
<td></td>
</tr>
<tr>
<td>2</td>
<td>Simulated Annealing (SA) [7]</td>
<td>709874.36</td>
<td></td>
</tr>
<tr>
<td>3</td>
<td>Genetic Algorithms (GA) [7]</td>
<td>709863.56</td>
<td></td>
</tr>
<tr>
<td>4</td>
<td>Evolutionary Programming (EP) [9]</td>
<td>709862.06</td>
<td></td>
</tr>
<tr>
<td>5</td>
<td>Hybrid EP method (HEP) [9]</td>
<td>710791.41</td>
<td></td>
</tr>
<tr>
<td>6</td>
<td>Proposed bacteria foraging algorithm</td>
<td>709862.00</td>
<td>2</td>
</tr>
</tbody>
</table>

Table 3 gives the comparison of results obtained for the test case using different optimization algorithms.

### Table 4
Optimal Hydrothermal Scheduling by Proposed Algorithm

<table>
<thead>
<tr>
<th>Time Interval</th>
<th>$P_{hy}$ (MW)</th>
<th>$P_{st}$ (MW)</th>
<th>Reservoir Storage Volume (V), m$^3$</th>
<th>Water Discharge Rate(q), m$^3$/hr</th>
<th>Generation Cost ($)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>303.801</td>
<td>896.199</td>
<td>101921.3 35938</td>
<td></td>
<td>709862.00</td>
</tr>
<tr>
<td>2</td>
<td>604.043</td>
<td>895.957</td>
<td>85936.23 4375</td>
<td></td>
<td>709862.00</td>
</tr>
<tr>
<td>3</td>
<td>203.765</td>
<td>896.235</td>
<td>93823.71 8750</td>
<td></td>
<td>709862.00</td>
</tr>
<tr>
<td>4</td>
<td>903.147</td>
<td>896.853</td>
<td>60000.06 2500</td>
<td></td>
<td>709862.00</td>
</tr>
<tr>
<td>5</td>
<td>161.180</td>
<td>788.5625</td>
<td>70427.26 6406</td>
<td></td>
<td>709862.00</td>
</tr>
<tr>
<td>6</td>
<td>510.853</td>
<td>789.147</td>
<td>60000.00 0000</td>
<td></td>
<td>709862.00</td>
</tr>
</tbody>
</table>

Table 4 gives the best optimal power output of thermal generator, hydro generator, storage volume and discharge for different time intervals obtained from proposed algorithm.

From the comparison of results, it is very clear that the proposed method can able to give global optimal solution and computation time of the proposed algorithm is very low compared with EP method and hybrid EP method.

Thus the potential of finding optimal solution with affordable time to the short term hydrothermal scheduling problem by proposed bacteria foraging algorithm is proved.

### 6. Conclusion

In this paper, new integrated bacteria foraging algorithm is proposed to solve the short term hydrothermal scheduling problem. When the problem is highly nonlinear, this algorithm out performs other algorithms in terms of the quality of the solution and computation expenses.

In phase 1 of the proposed algorithm, bacteria foraging algorithm is used to narrow down the solution space and in phase 2 the local searches are applied to locate the global optimal solution. For the example problem, the convergence of bacteria foraging algorithm is verified and the reliability of the proposed method is tested for 50 runs.

From the results it is proved that the proposed algorithm can be applied to short term hydrothermal scheduling problem and can obtain the global optimal solution with lesser computation time.

### Acknowledgements

The authors are very thankful to the authorities of Dr. Pauls Engineering College, villupuram (Dist), K.S,Rangasamy College of Technology, Thiruchengode and Pondicherry Engineering College, Pondicherry for providing all facilities to complete this piece of work.

### References


