Optimization of Tie-Line Power in Automatic Generation Control of Interconnected Thermal-Hydro Power System using (BFO+PSO)

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***Abstract*:- A maiden attempt is made to examine and highlight the effective application of bacteria foraging particle swarm optimization (BFO+PSO) to optimize the tie-line power variation in automatic generation control of interconnected two area thermal-hydro power system. The variation in a tie-line power can be reduced to a nominal value or zero value by using application of bacteria foraging particle swarm optimization (BFO+PSO). It is a combination of bacteria foraging optimization and particle swarm optimization to settle down the variation in tie-line power to nominal value in reduced settling time as compared to bacteria foraging and particle swarm optimization. Bacteria foraging particle swarm optimization (BFO+PSO) not only give much reduced settling time but also give best dynamic response.**

Keywords:- Automatic generation control (AGC), Bacteria foraging particle swarm optimization (BFO+PSO) algorithm, Sensitivity analysis.

I. INTRODUCTION

In actual power system operations, the load is changing continuously and randomly. As a result the real and reactive power demands on the power system are never steady, but continuously vary with the rising or falling trend. The real and reactive power generations must change accordingly to match the load perturbations. Automatic generation control is essential for successful operation of power systems, especially interconnected power systems. Without it the frequency of power supply may not be able to be controlled within the required limit band. To accomplish this, it becomes necessary to automatically regulate the operations of main steam valves in accordance with a suitable control strategy, which in turn controls the real power output of electric generators. Thus the main objective of the power system is to maintain continuous supply of power with an acceptable quality, to all the consumers in the system. In case of an interconnected power system having two or more areas connected through tie lines, each area supplies its control area and tie lines allow electric power to flow among the areas. However, a load perturbation in any of the areas affects output frequencies of all the areas as well as the power flow on tie lines. Hence the control system of each area needs information about transient situation in all the other areas to restore the nominal values of area frequencies and tie line powers. The information about each area is found in its output frequency and the information about other areas is in the deviation of tie line powers. For example, for a two area interconnected power system, this information is taken as

$$B_i \delta f_i + \delta P_{tie} \quad (i = 1,2,\ldots S) \quad \ldots\ldots(1)$$

Where, B = tie line frequency bias, f = nominal frequency, Ptie = tie line power

Equation1.Refers the area control error (ACE) and the same is fed as input to the integral controller of corresponding area. Thus an AGC scheme for an interconnected power system basically incorporates suitable control system, which can bring the area frequencies and tie line powers back to nominal or very close to nominal values effectively after the load perturbations. A lot of literature is available on load frequency control of isolated and interconnected electrical power systems using various classical and intelligence technique like pi, pid, fuzzy, neural network, genetic algorithm, particle swarm optimization, bacteria foraging optimization etc. For any optimization technique both the convergence and optimal value achieved are important. When we apply a hybrid combination of both bacteria foraging optimization and particle swarm optimization to interconnected thermal-hydro power system then it give not only more reduced settling time to settle power variation in tie-line power to a nominal value but also give best dynamic response as compared to BFO and PSO technique alone.

II. BACTERIA FORAGING OPTIMIZATION

This technique is based upon the foraging behavior of e.coli bacteria. In this technique four main step are done which are chemotactic, swarming, reproduction and elimination & dispersal step.

A. Bacteria foraging algorithm:-

Step 1 Initialization

1. Number of parameters (p) to be optimized;
2. Number of bacteria (S) to be used for searching the total region;
3. Swimming length (Ns) after which tumbling of bacteria will be undertaking in a chemotactic;
4. Nc is the number of iterations to be undertaken in a chemo tactic loop (Nc > Ns)

5. Nre is the maximum number of reproduction to be undertaken;
6. Ned is the maximum number of elimination and dispersal events to be imposed over the bacteria;
7. P_{ed} the probability with which the elimination and dispersal will continue.
8. The location of each bacterium P(1-p,1-S,1) which is specified by random numbers on [1, 1];
9. The value of C(i) which is assumed to be constant in our case for all of the bacteria.

Step 2 Iterative Algorithms for Optimization

This section models the bacterial population chemo taxis, swarming, reproduction, elimination, and dispersal (initially, j=k=el=0). For the algorithm updating θ^i automatically result in updating of "P".

1. Elimination-dispersal loop : el=el+1
2. Reproduction loop : k=k+1
3. Chemotaxis loop : j=j+1

 i. For i=1, 2, 3,---S take a chemotactic step for bacteria I as follows.

 ii. Compute cost function, j (i, j, k, el).

 iii. Let, J(i, j, k, el) = J(i, j, k, el) + $J_{cc}(\theta^i$ (j, k, el),P(j, k, el)) (i.e. add on the cell to cell attractant-repellant profile to simulate the swarming behavior) where J_{cc} is the objective function value to be added to the actual objective function value to be minimized.

 iv. Let, J_{last} =J(i, j, k, el) to save this value since we may find a better cost via a run.

 v. Tumble: generate a random vector δ(i) with each element $\delta_m(i)$, m= 1,2,…,p.

 vi. Move: let

 Θ^i (j+1, k, el) = θ^i (j, k, el) + C(i)δ(i)/√δ(i) $\delta(i)^*$

 This result in a step of size C(i) in the direction of tumble for bacterium i.

 vii. Compute J(i, j+1, k, el) and let,

 J(i, j+1, k, el) = J(i, j, k, el) + J_{cc} (θ^i (j+1, k, el),P(j+1, k, el))

 viii. Swim:

 - Let m=0 (counter for swim length).

 While m<N_s

 - Let m= m+1

 If J (i, j+1, k, el) < J_{last} and let J_{last} =

 J (i, j+1, k, el) and let

 Θ^i(j+1, k, el) = θ^i(j, k, el) + C(i)δ(i)/ √δ(i) $\delta(i)^*$

 And use this Θ^i (j+1, k, el) to compute the new J (i, j+1, k, el)

 Else, let m = Ns, this is the end of while statement.

 ix. Go to next bacterium (i+1) if i± S (i.e., go to (ii) to process the next bacterium.

4. If J<Nc go to step 3. In this case continue chemotaxis since the life of bacteria is not over.
5. Reproduction:

 I. For a given k and el , and for each I = 1, 2,…,S , let

 i. J_{health} $\sum_{j=1}^{Nc+1} J(i,j,k,el)$

 ii. Be the health of bacteria i. Sort bacteria and chemotactic parameter C(i) in order of ascending cost J_{health} (higher cost means lower health).

 II. The S_r bacteria with the highest J_{health} value die and the remaining S_r bacteria with the best value split .

6. If k<N_{re}, go to step 2. In this case we have not reached the number of specified reproduction step , so we start the next generation of the chemotactic loop.
7. Elimination-dispersal: For i = 1, 2…..,S with probability p_{ed} , eliminate and disperse each bacterium To do this if a bacterium is eliminated , simply disperse another one to a random location on the optimization domain. If el < Ned then go to step 2; otherwise end.

III. PARTICLE SWARM ALGORITHM

A basic variant of the PSO algorithm works by having a population (called a swarm) of candidate solution (called particles). These particles are moved around in the search-space according to a few simple formulae. The movements of the particles are guided by their own best known position in the search-space as well as the entire swarm's best known position. When improved positions are being discovered these will then come to guide the movements of the swarm. The process is repeated and by doing so it is hoped, but not guaranteed, that a satisfactory solution will eventually be discovered. Formally, let $f: \mathbb{R}^n \rightarrow \mathbb{R}$ be the cost function which must be minimized. The function takes a candidate solution as argument in the form of a vector of real number and produces a real number as output which indicates the objective function value of the given candidate solution. The gradient of f is not known. The goal is to find a solution **a** for which f(**a**) ≤ f(**b**) for all **b** in the search-space, which would mean **a** is the global minimum. Maximization can be performed by considering the function $h = -f$ instead.

Let S be the number of particles in the swarm, each having a position $\mathbf{x}_i \in \mathbb{R}^n$ in the search-space and a velocity $\mathbf{v}_i \in$

$\mathbb{R}^n$. Let $\mathbf{p}_i$ be the best known position of particle *i* and let **g** be the best known position of the entire swarm. A basic PSO algorithm is then

1. For each particle $i = 1, ..., S$ do:
   a. Initialize the particle's position with a uniformally distributed random vector: $\mathbf{x}_i \sim U(\mathbf{b}_{lo}, \mathbf{b}_{up})$, where $\mathbf{b}_{lo}$ and $\mathbf{b}_{up}$ are the lower and upper boundaries of the search-space.
   b. Initialize the particle's best known position to its initial position: $\mathbf{p}_i \leftarrow \mathbf{x}_i$
   c. If $(f(\mathbf{p}_i) < f(\mathbf{g}))$ update the swarm's best known position: $\mathbf{g} \leftarrow \mathbf{p}_i$
   d. Initialize the particle's velocity: $\mathbf{v}_i \sim U(-|\mathbf{b}_{up}-\mathbf{b}_{lo}|, |\mathbf{b}_{up}-\mathbf{b}_{lo}|)$
2. Until a termination criterion is met (e.g. number of iterations performed, or a solution with adequate objective function value is found), repeat:
   a. For each particle $i = 1, ..., S$ do:
      i. Pick random numbers: $r_p, r_g \sim U(0,1)$
      ii. For each dimension $d = 1, ..., n$ do:
         1. Update the particle's velocity: $\mathbf{v}_{i,d} \leftarrow \omega\ \mathbf{v}_{i,d} + \varphi_p\ r_p\ (\mathbf{p}_{i,d}-\mathbf{x}_{i,d}) + \varphi_g\ r_g\ (\mathbf{g}_d-\mathbf{x}_{i,d})$
      iii. Update the particle's position: $\mathbf{x}_i \leftarrow \mathbf{x}_i + \mathbf{v}_i$
      iv. If $(f(\mathbf{x}_i) < f(\mathbf{p}_i))$ do:
         1. Update the particle's best known position: $\mathbf{p}_i \leftarrow \mathbf{x}_i$
         2. If $(f(\mathbf{p}_i) < f(\mathbf{g}))$ update the swarm's best known position: $\mathbf{g} \leftarrow \mathbf{p}_i$
3. Now **g** holds the best found solution.

The parameters ω, φ_p, and φ_g are selected by the practitioner and control the behaviour and efficacy of the PSO method.

The optimal position of bacteria obtained by bacteria foraging optimization (BFO) is used as a local position of bacteria population which is also called candidate solution in particle swarm optimization in search space. The local position of bacteria population is initial position of bacteria position in search space which is updated using particle swarm optimization algorithm to find the best known position of bacteria in search space, if the best position of bacteria swarm is less than the global best known position of bacteria swarm then we update the position of bacteria position in search space to obtain global best position of bacteria swarm in search space.

For automatic generation control the objective function is taken as:-

$$J = \int_0^T \{(\Delta Fi)^2 + (\Delta Ptie - j)^2\}\ dt$$

IV. TABLE AND FIGURE

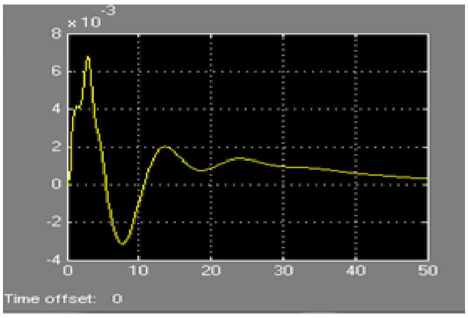

Fig.1 Shows the Relation b/w Δ P_{tie} and time for Thermal power plant PI Controller only

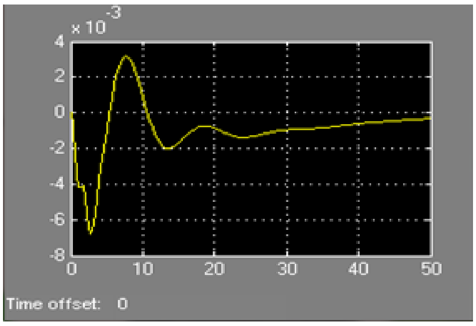

Fig.2 Show the Relation B/w Δ P_{tie} and time for hydro power plant PI Controller only

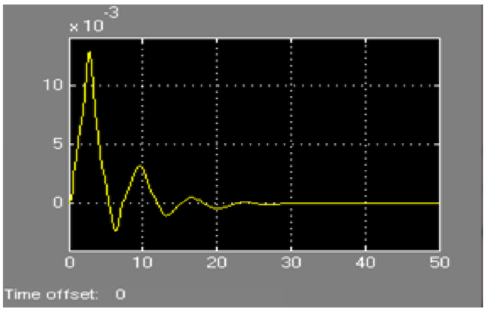

Fig.3 Shows the Relation B/w Δ P_{tie} and time for Thermal Power Plant Using PI controller and BFO

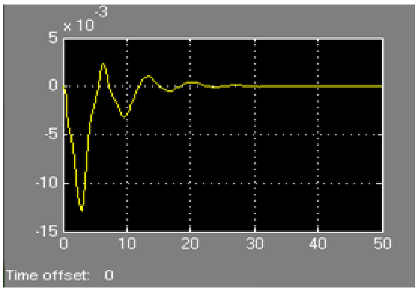

Fig.4 Shows the Relation B/w Δ P_{tie} and time for Hydro power plant Using PI Controller and BFO

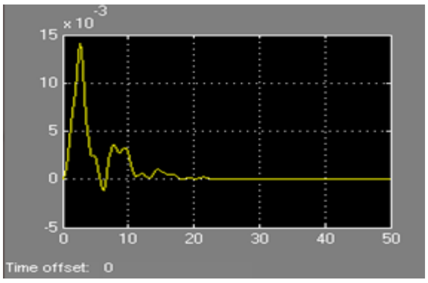

Fig.5 Shows the Relation B/w Δ P_{tie} and time for thermal Power Plant using PI Controller and (BFO+PSO)

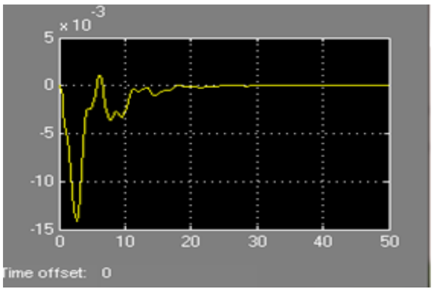

Fig.6 Showsthe Relation B/w Δ P_{tie} and time for Hydro Power Plant using PI Controller and (BFO+PSO)

Table 1

PARAMETER	PI CONTROLLER	BFO	BFO+PSO
CONTROLLER GAIN (Ki1)	0.1010	1.5575	2.1510
CONTROLLER GAIN (Ki2)	0.0510	0.1301	0.1001
SETTLING TIME (TS)	50(S)	25(S)	18(S)
INTEGRAL SQUARE ERROR	7.41(max)	0.0021(max)	0.0027(max)

V. CONCLUSION

When we apply the application of bacteria foraging particle swarm optimization (BFO+PSO) algorithm to an interconnected thermal-hydro power plant then the result reveal that tie-line power variation (ΔP_{tie}) can be reduced to nominal value or zero value in less consumption time as compared to bacteria foraging optimization and particle swarm optimization alone. The performance index (J) is also reduced to lower value and controller gains of thermal and hydro power plant are optimized in such a way that AGC give less variation in tie-line power and load frequency.

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