Chaotic Particle Swarm Optimization for Reduced Order Model of Automatic Generation Control

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Abstract— this paper proposed a new approach to control frequency and tie line power changes of multi area interconnected system. The proposed approach uses a different set of assumptions from that conventionally used. This method can preserve the identity of each generating unit. With this method, the computational complexity has been reduced by resorting the lower order generating unit models. In this paper, model order reduction technique has been used to obtain lower order model for study of automatic generation control (AGC). AGC is very important in power system to maintain system frequency and tie-line power, when system subjects to small load perturbations. To obtain better transient performance with reduced model of AGC a chaotic particle swarm optimization (CPSO) algorithm is used for optimization. The proposed method shows its robustness under critical conditions when conventional optimization methods fail. CPSO is used to optimize gains of PI controller and bias frequency, to maintain system frequency and tie-line power flow at scheduled values. This paper also presents the selection of suitable value for governor speed regulation parameter.

NOMENCLATURE

\[ \Delta F = \text{Frequency deviation.} \]
\[ i = \text{Subscript referring to area (i = 1,2,……).} \]
\[ \Delta P_{tie} (i,j) = \text{Change in tie line power.} \]
\[ \Delta P_{di} = \text{Load change of } i^{th} \text{ area.} \]
\[ D_i = \Delta P_{di} / \Delta F_i \]
\[ R_i = \text{Governor speed regulation parameter for } i^{th} \text{ area.} \]
\[ T_{bi} = \text{Speed governor time constant for } i^{th} \text{ area.} \]
\[ T_u = \text{Speed turbine time constant for } i^{th} \text{ area.} \]
\[ T_{pi} = \text{Power system time constant for } i^{th} \text{ area.} \]
\[ K_p = \text{Power system gain for } i^{th} \text{ area.} \]
\[ ACE_i = \text{Area control error of } i^{th} \text{ area.} \]
\[ H_i = \text{Inertia constant of } i^{th} \text{ area.} \]
\[ U_i = \text{Control input to } i^{th} \text{ area.} \]
\[ B_i = \text{Frequency bias for } i^{th} \text{ area.} \]
\[ U = \text{Undershoot of ACE.} \]
\[ Mp = \text{Overshoot of ACE.} \]
\[ ts = \text{Settling time of ACE.} \]
\[ tr = \text{Rise time of ACE.} \]

\[ \text{ess} = \text{Steady state error of ACE.} \]
\[ W = \text{Inertia weight.} \]
\[ C_1, C_2 = \text{acceleration coefficient.} \]

I. INTRODUCTION

AUTOMATIC generation control is one of the most important issues in power system design. The purpose of AGC is fast minimization of area frequency deviation and mutual tie-line power flow deviation of areas for stable operation of the system.

The overall performance of AGC in any power system is depends on the proper design of speed regulation parameters and gains of controller. Fixed linear feedback controller fails to provide best control performance. There all no well defined method is available to compute tie-line constant for an area with non-coherent generators and multiple tie-line. These papers evolve an AGC simulation technique that overcomes this problem. This assumption overcome the need of identify the non-coherent set of generators in order to the control areas. These assumptions follow the fact that, all areas are operating at same frequency and tie-line flow can no longer be computed in actual system. Tie-line flows are required to determine area control error [3].

This scheme increases the computational effort. The reduced order model is applied on generating units. This reduced order model has approximately same response as full order models. The reduced order is demonstrated by optimization of controller. Since the conventional controller improve steady state error (ess) but with small overshoot. PI controller has such capability to improve transient performance with minimum steady state error.

The aim of this paper is to find optimum gains of PI controller and frequency bias with proper system parameter for reduced order system. CPSO is a stochastic based algorithm to solve a problem. It provides more prescribe description of natural swarm behavior. CPSO is an optimization approach based on the PSO with adaptive inertia weight factor methods.

In the view of the above, following are main objectives of the proposed paper:

1. To reduced the order of the generating unit of AGC system.
2. To optimized the gains of PI controller and frequency bias coefficient using chaotic PSO algorithm.
3. To examine the effect of speed regulation parameters on reduced system.

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The rest of the paper is organized as follow: In section II AGC system model with proposed reduction technique is developed. In section III describe chaotic particle swarm optimization in brief and implement PDPSO based PI controller in section IV. Section V shows the result with discussion and conclusion is drawn in section VI.

II. SYSTEM MODEL

A. Conventional AGC system

Automatic control system of close loop system means minimizing the area control error (ACE) to maintain system frequency and tie-line deviation are set at nominal value [15]. Block diagram of two area system is shown in fig. 1.

![Block diagram of two area system](image)

Fig.1: linear model of two area system.

The ACE of each area is linear combination of biased frequency and tie-line error.

\[
ACE_i = \sum_{j=1}^{n} (\Delta P_{tie(i,j)} + B_i \Delta F_i)
\]

(1)

Where, B_i is frequency bias coefficient of i\(^{th}\) area. \(\Delta F_i\) is frequency deviation and \(\Delta P_{tie}\) is tie-line error of i\(^{th}\) area. The area bias determines the amount of iteration duration load perturbation in neighboring area.

Based on the ACE a suitable control strategy can be taken either continuously or discretely. A practical system consist a number of generating units, Therefore computational time and complexity increases. Thus the reduction of order is introduced to reduce this effort.

B. Reduced order generating unit

Several methods are available for reducing the order of a system transfer function (TF) [14]. One way is to delete a certain insignificance pole of a transfer function, which has a negative real part that is much more negative than the other poles [14]. An effective approach is to match the frequency response of the reduced order transfer function with the original TF frequency response. Suppose the higher order system is described as:

\[
G_H(s) = K \frac{a_m s^m + a_{m-1} s^{m-1} + \cdots + a_1 s + a_0}{b_n s^n + b_{n-1} s^{n-1} + \cdots + b_0}
\]

(2)

This system has poles in the left hand s-plane and m ≤ n. The lower order approximate transfer function is:

\[
G_L(s) = K \frac{c_p s^p + c_{p-1} s^{p-1} + \cdots + c_1 s + c_0}{d_q s^q + d_{q-1} s^{q-1} + \cdots + d_0}
\]

(3)

Where p ≤ q ≤ n. The gain K is the same for original and approximated system. This method is based on selection of c and d in such a way that \(G_L(s)\) has a response very close to that of \(G_H(s)\). These coefficients are evaluated as:

\[
M(q, s) = \frac{d^q M(s)}{ds^q}
\]

(4)

And

\[
\Delta(q, s) = \frac{d^q \Delta(s)}{ds^q}
\]

(5)

Where, M(s) and \(\Delta(s)\) are the numerator and denominator polynomials of \(G_H(s)/G_L(s)\) respectively. Also define

\[
M_{2q} = \sum_{i=1}^{\infty} (-1)^{i+q} M(i)(0) M(2q+1)(0)
\]

(6)

q=0, 1, 2, ---- up to number required to solve the unknown coefficients. An analogous equation for \(\Delta_{2q}\) the solution for c and d coefficient is obtained by equating \(M_{2q} = \Delta_{2q}\).

In this paper two area AGC system is considered. This model has second order transfer function of generating unit of each area as:

\[
G_L(s) = \frac{1}{(1 + sT_H)(1 + sT_L)}
\]

(7)

The value of AGC parameters (T_H and T_L) are given in appendix.

After reduction as above method the lower order generating unit becomes:

\[
G_L(s) = \frac{-0.1451 s + 2.965}{s + 2.965}
\]

(8)

III. OVERVIEW OF CHAOTIC PARTICLE SWARM OPTIMIZATON

A. General PSO method

Particle swarm optimization (PSO) first proposed by Kennedy and Eberhart [5]. Like evolutionary algorithms, PSO techniques conducts search using a population of particles, corresponding to individuals. In PSO, particles changes their position by flying around in a search space until computation limitations are exceed. PSO is inspired by the ability of flocks of birds. In PSO each particle is defined as moving part in hyperspace. PSO is inherently continuous and must be modified to handle design variables.

The basic PSO algorithm requires three steps, namely, generation of particles, positions and velocities,
second, update and third, position update [5]. PSO is initialized with the group of random particle positions \( \{x_i\} \) and velocities \( \{v_i\} \) between upper and lower bound of design variable values as expressed in equation 4.

\[
X_i^t = X_{\text{min}} + \text{rand} \times (X_{\text{max}} - X_{\text{min}})
\]  

(9)

The second step is to update velocities of all particle positions for next \((k+1)\) iteration using the particle’s fitness values which is function of particle positions. These fitness function value determines which particle has a global best (gbest) value in the current swarm (iteration) and also determine the best position (pbest) of each particles.

The global best value fast the rate of convergence. This value maintains only single best solution across the entire particle in the search space. If all particles are converge to this position, so it is not update regularly.

After finding the two best values, the particles update its velocity and positions using following equation:

\[
v_{k+1}^i = w v_k^i + c_1 r_1 (pbest^i - x_k^i) + c_2 r_2 (gbest_k - x_k^i)
\]  

(10)

Where \( w \) is inertia weight factor, \( c_1 \) and \( c_2 \) are self confidence and swarm confidence respectively. Combinations of these values usually lead to much slower convergence or sometimes non-convergence at all.

Now positions of particles are updated using following equation:

\[
x_{k+1}^i = x_k^i + v_{k+1}^i
\]  

(11)

B. Chaotic PSO

The parameters \( r_1 \) and \( r_2 \) in equation (10) are important control parameters. The use of chaotic sequence in PSO can be useful to escape from local minima than general PSO [4].

Chaotic sequence based on H’enon mapping is used as:

\[
y(t) = 1 - ay(t - 1) + z_1(t - 1)
\]  

(12)

\[
z_1(t) = by(t - 1)
\]  

(13)

Where, ‘a’ and ‘b’ are H’enon map attractor. Another mapping uses the same equation to generate \( z_2(t) \) in range \([0, 1]\). Other parameters are same as in equation (10). Hence, velocity of particle is updated as:

\[
v_{k+1}^i = w v_k^i + c_1 z_1 (pbest_k^i - x_k^i) + c_2 z_2 (gbest_k - x_k^i)
\]  

(14)

IV. IMPLEMENTATION OF CPSO-PI CONTROLLER

A. Fitness function

The gain of PI controller can be selected from degree of relative stability, minimum overshoot, undershoot and settling time. To satisfy all requirements following objective function is design.

\[
J = (Mp + ess) \times 1000 + (Us.100)^2 + (ts - tr)^2
\]  

(15)

B. Algorithm

Step1. Choose the population size and number of iteration.

Step2. Generate initial velocities as:

\[
v^i = 0.4 \times \text{rand} (v_{\text{max}} - v_{\text{min}})
\]  

(16)

Step3. Run model of reduced AGC system and determine performance parameters for each particle.

Step4. Calculate fitness function (eq.15).

Step5. Calculate gbest and pbest position value. Using these values calculate velocity of each particle (eq.14).

Step6. Update position of each particle (eq. 11).

Step7. If the number of iteration since the last change of the best solution is greater than a pre specified number or the number of iteration reaches the maximum iteration, stop the process.

V. RESULT AND DISCUSSION

The reduced order AGC model is obtained by using above procedure. The effectiveness of this reduced model has been investigated. Comparison of full order (actual) and reduced order AGC model is given in table-I for input data set1 (\( Tp=10, R=8\% \) frequency, \( T12=0.145 \)). It shows that reduced order model has less computational time than full order model with approximately same performance parameters.

To provide a comparison of these approach, the time response plots of the reduced order as well as full order AGC system is given in fig.2. These figures show the variation in system frequency, tie-line power flow and area control error for 1% step load perturbation area two. From these figures it can be seen that the response of reduced order generating unit model and actual model are approximately identical. Hence, lower order model can be used to obtain desired response.

The gains of PI controller and frequency bias are obtained by chaotic PSO algorithm for different value of system parameters of reduced order AGC system. As fig. 16-20 shows, PI controller act too fast to the generator inputs and also exhibits fast oscillations. In all cases, an acceptable overshoot and settling time on frequency deviation signal in each area is maintained.

Table-II gives transient response parameters of CPSO based PI controller for different data set. Input data set2 have (\( Tp=30, R=8\% \) of frequency, \( T12=0.145 \)) and data set3 have (\( Tp=30, R=4\% \) of frequency, \( T12=0.145 \)). Table-II and figures 6-9 shows that the large values of power system time constant (\( Tp=30 \)) and low value of \( T12 \) (0.145) yield large value of undershoot, overshoot and settling time and hence high value of fitness function. Fig10-13 show that these values (undershoot, overshoot, settling time) become lower as speed regulation, \( R \) decreases from 8\% to 4\% of frequency.
The initial sharp in undershoot and overshoot lies due to choice of weighting factor (1000 and 100) in the fitness function.

Table-I comparison of actual and reduced order system for data set-I

<table>
<thead>
<tr>
<th>AGC model</th>
<th>Optimal PI gain and freq, bias</th>
<th>( M_\text{p} )</th>
<th>( U_\text{s} \times 10^4 )</th>
<th>( T_\text{S} )</th>
<th>Fitness function</th>
<th>Computational time in sec.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Full order (actual)</td>
<td>1.0171</td>
<td>0.4219</td>
<td>0.1439</td>
<td>0.0014</td>
<td>-9.65</td>
<td>26.1033</td>
</tr>
<tr>
<td>Reduce order</td>
<td>1.0179</td>
<td>0.4223</td>
<td>0.1448</td>
<td>0.0012</td>
<td>-8.795</td>
<td>24.215</td>
</tr>
</tbody>
</table>

Table-II comparison of effect on input system parameters on reduced order AGC system.

Dataset1 (\( T_p=10, R=8\% \text{ of freq}, T_{12}=0.145 \)).
Dataset2 (\( T_p=30, R=8\% \text{ of freq}, T_{12}=0.145 \)).
Dataset1 (\( T_p=30, R=4\% \text{ of freq}, T_{12}=0.145 \)).

<table>
<thead>
<tr>
<th>Input parameter bias</th>
<th>Optimal PI gain and freq, bias</th>
<th>( M_\text{p} )</th>
<th>( U_\text{s} \times 10^4 )</th>
<th>( T_\text{S} )</th>
<th>( E_{ss} \times 10 )</th>
<th>Fitness function</th>
</tr>
</thead>
<tbody>
<tr>
<td>Dataset1</td>
<td>1.0179</td>
<td>0.4223</td>
<td>0.1448</td>
<td>0.0012</td>
<td>-8.795</td>
<td>24.215</td>
</tr>
<tr>
<td>Dataset2</td>
<td>0.197</td>
<td>0.7073</td>
<td>0.1917</td>
<td>0.0022</td>
<td>-0.0030</td>
<td>26.1348</td>
</tr>
<tr>
<td>Dataset3</td>
<td>0.5343</td>
<td>0.7846</td>
<td>0.9216</td>
<td>0.0010</td>
<td>-0.0014</td>
<td>11.3281</td>
</tr>
</tbody>
</table>

Fig2. Variation in area control error in reduced order and full order system

Fig3. Comparison of tie-line power for reduced order and full order AGC system

Fig4. Comparison of area frequency 1 for reduced order and actual system.

Fig5. Comparison of area frequency 2 for reduced and actual system

Fig6. Variation in area control error in dataset1 and dataset2
VI. CONCLUSION

In this paper a reduced order AGC system is proposed. This system overcomes the difficulties associated with large interconnected system by preserving the identity of each generating unit. This approach reduced the effective time of computation with identical response.

In this paper CPSO method is used to obtain optimum gains of PI controller and frequency bias coefficient. CPSO is new variant of PSO with faster speed because of strong selection principle.

In simple PSO, after certain iterations, the populations set are almost identical and no further improvement is observed.

Like any other algorithms, this method also somewhat sluggish in nature but positive aspect of this method is its reliability and the number of required generation for convergence decreases with increase of population size.
APPENDIX

Nominal parameters of two area test system [15]:
H₁ = H₂ = 5 seconds
D₁ = D₂ = 8.33x10⁻³ P.U. MW/Hz
R₁ = R₂ = 2.4 Hz/P.U. MW
Th₁ = Th₂ = 80 ms
Tt₁ = Tt₂ = 0.3 seconds
Kp₁ = Kp₂ = 120 Hz P.U. MW

Parameters for CPSO:
Population size = 20
Number of iteration = 100
C₁ = C₂ = 1.5
W_min = 0.6
W_max = 1

REFERENCES
[1] Zhihua Cui, Xingjuan Cai and Jianchao zeng, “Chaotic performance dependent particle swarm optimization.” Division of system simulation and computer application Taiyuan University of science and technology.