AGC TUNING OF INTERCONNECTED REHEAT THERMAL SYSTEMS WITH PARTICLE SWARM OPTIMIZATION

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ABSTRACT

This paper demonstrates the use of particle swarm optmization for optimizing the parameters of automatic generation control systems (AGC). An integral controller and a proportional-plus-integral controller are considered. A two-area reheat thermal system is considered to exemplify the optimum parameter search. The optimal AGC parameters search is formulated as an optimization problem with a standard infinite time quadratic objective function. A time domain simulation of the system is then used in conjunction with the particle swarm optimizer to determine the controller gains. The integral square of the error and the integral of time-multiplied absolute value of the error performances indices are considered. The results reported in this paper demonstrate the effectiveness of the particle swarm optimizer in the tuning of the AGC parameters. The enhancement in the dynamic response of the power system is verified through simulation results.

1. INTRODUCTION

Many investigations have been reported in the past pertaining to automatic generation control (AGC) of a large interconnected power system. A net interchange tie-line bias control strategy has been widely accepted by utilities. The frequency and the interchanged power are kept at their desired values by means of feedback of the area control error (ACE) integral, containing the frequency deviation and the error of the tie line power, and controlling the prime movers of the generators.

The controllers so designed regulate the area control error to zero. For each area, a bias constant determines the relative importance attached to the frequency error feedback with respect to the tie-line power error feedback; the bias is very often equal to the natural area frequency response characteristic [1-4]. Classical AGC corresponds basically to industry practice for the past years or so. The key assumptions are:

(a) The steady-state frequency error following a stepload change should vanish. The transient frequency and time errors should be small.

- (b) The static change in the tie power following a step load in any area should be zero, provided each area can accommodate its own load change.
- (c) Any area in need of power during emergency should be assisted from other areas.

The key advantage of the classical AGC is that the control strategy is a totally decentralized one, in the sense that each control area carries out its own frequency and power regulation using locally gathered real-time information.

The transient performance of the interconnected power system with respect to the control of the frequency and tie line powers obviously depends on the value of the integral gain and the frequency bias. The optimum parameter values of the classical AGC have been obtained in the literature by minimizing the popular integral of the squared error criterion (ISE) [4]. This criterion, although not very selective, has been used because of the ease of computing the integral both analytically and experimentally. A system designed by this criterion is oscillatory with poor relative stability.

In this work, we seek the optimum adjustment of the classical AGC parameters using particle swarm optimization [5,6] and two objective functions which are functions of error and time. These are the integral of the square of the error criterion (ISE), and the integral of time-multiplied absolute value of the error criterion (ITAE)[7]. The latter penalizes long-duration transients and is much more selective than the ISE.

A digital simulation is used in conjunction with the particle swarm optimization process to determine the optimum parameters of the AGC for each of the objective functions considered. Particle swarm optimization (PSO) features many advantages; it is simple, fast and can be coded in few lines. Also, its storage requirement is minimal.

An interconnected two-area reheat thermal system is considered in this paper to demonstrate the suggested technique. In addition to the conventional AGC, a more elaborate feedback control strategy, namely the proportional-plus-integral control is also investigated. In this case the feedback control signal is a linear combination of the ACE and its integral. The enhancement in the dynamic response of the power system is verified through time domain simulation

2. PARTICLE SWARM OPTIMIZATION

Particle swarm optimization is similar to other evolutionary computation techniques in conducting searching for optima using an initial population of individuals. The individuals of this initial population are then updated according to some kind of process such that they are moved to a better solution area. The four well-known evolutionary algorithms, namely, genetic algorithm, evolutionary programming, evolutionary strategies, and genetic programming are motivated by evolutionary seen in nature. They borrow the principle of competition and survival of the fittest from there. PSO, on the other hand, is motivated form the simulation of social behavior. It borrows the principle of cooperation and competition among the individual themselves.

However, this approach is advantageous over evolutionary and genetic algorithms in more than one way. First, PSO has memory. That is, every particle remembers its best solution (local best) as well as the group best solution (global best). Another advantage of PSO is that the initial population of the PSO is maintained, and so there is no need for applying operators to the population, a process which is time- and memory-storage-consuming.

In PSO system, each individual adjusts its flying in a multi-dimensional search space according to its own flying experience and its companions flying experience. Each individual is referred to as a "particle" which represents a candidate solution to the problem. Each particle is treated as a point in a *D*-dimensional space. The *i*th particle is represented as $X_i = (x_{i1}, x_{i2}, x_{i3}, ..., x_{iD})$. The best previous position (giving the best fitness value) of any particle is recorded and represented as $P_l = (P_{i1}, P_{i2}, P_{i3}, ..., P_{iD})$ The index of the best particle among all the particles in the population is represented by the symbol g. The rate of the position change (velocity) for particle *i* is represented as $.V_i = (V_{i1}, V_{i2}, V_{i3}, ..., V_{iD})$ The particles are manipulated according to the following equation [8]:

$$V_{id} = V_{id} + c_1 r_1 (P_{ld} - X_{id}) + c_2 r_2 (P_{gd} - X_{id})$$
(1)

$$X_{id} = X_{id} + V_{id} \tag{2}$$

where c_1 and c_2 are positive constants and r_1 and r_2 are uniformly distributed random numbers in [0,1].

3. LOAD FREQUENCY CONTROL PROBLEM

The block diagram representation of a two-area reheat thermal system is shown in Figure 1 [3].



Figure 1. Model of a two-area reheat thermal system

where

| ΔP_{Gi} | incremental generation change |
|-------------------|---|
| ΔX_{Ei} | incremental governor valve position change |
| ΔP_{Di} | incremental load demand change |
| Δf_i | incremental frequency deviation |
| ΔP_{tiei} | incremental change in tie-line power |
| ΔP_{ci} | incremental change in speed changer position |
| f | nominal system frequency |
| H_i | inertia constant |
| D_i | load frequency constant |
| | $\left(K_{pi} = \frac{1}{D_i}, T_{pi} = \frac{2H_i}{fD_i}\right)$ |
| T_{Ri} | reheat time-constant |
| K_{Ri} | reheat coefficient |
| T_{ij} | synchronizing coefficient |
| R_i | speed regulation parameter |
| T_{Gi} | governor time-constant |
| T_{Ti} | turbine time constant |
| | |

The area control error (ACE) for the i^{th} area is defined as

$$ACE_i = \Delta P_{tiei} + B_i \Delta f_i \tag{3}$$

Two control systems are considered. The first one features the conventional AGC with an integral control strategy of the form:

$$\Delta P_{ci} = -K_{Ii} \int (\Delta P_{tiei} + B_i \Delta f_i) dt \tag{4}$$

The second system is of the proportional-plus-integral type. In this case, the control signal is given by:

$$\Delta P_{ci} = K_{PRi} (ACE_i) - K_{Ii} \int (ACE_i) dt$$
(5)

where

 B_i frequency bias constant K_{Ii} integral gain $K_{PR,i}$ proportional gain In this study, the optimum values of the controller parameters, which minimize the objective function, are accurately computed using particle swarm optimization.

In a typical run of the PSO, an initial pouplation of random solutions is generated. Each particle keeps track of its coordinates in hyperspace which are associated with the fittest solution it has achieved so far. The value of the objective function, P_l , is also stored. Another best value is also tracked. The global version of the PSO keeps track of the overall best value, and its location, obtained thus far by any particle in the population, which is called P_g . The PSO, at each step, changes the velocity and the position of each particle toward its P_l and P_g .

The application of PSO involves repetitively performing two steps:

- 1. The calculation of the objective function for each of the particles in the current population. To do this, the system must be simulated to obtain the value of the objective function.
- 2. The particle swarm optimization then updates the particle coordinates based on equations (1) and (2).

These two steps are repeated from population to population until a stoping criterion terminates the search producing the optimum gains .The following PSO parameters were used in the present study: Number of particles =20, $c_1 = 4.0$, $c_2 = 4.0$

To simplify the analysis, the two interconnected areas were considered identical. Thus,

 $K_{I1} = K_{I2} = K_I$; $B_1 = B_2 = B$; $K_{PR1} = K_{PR2} = K_{PR}$ The nominal system parameters are [4] $D = 8.33 \times 10^{-3}$ pu MW/Hz, H = 5 sec $P_r = 2000$ MW (area rated capacity) $P_{tie \max} = 200$ MW (tie-line capacity)

 $T_{12} = \frac{P_{tie \text{ max}}}{P_r} \cos 30^\circ$, $K_R = 0.5$, $T_R = 10 \text{ sec}$ R = 2.4 Hz/pu MW, $T_G = 0.08 \text{ sec}$, $T_T = 0.3 \text{ sec}$ $K_p = 120 \text{ Hz/pu MW}$, $T_p = 20 \text{ sec}$

The objective functions considered in this study are of the form:

$$J_1 = \int_{0}^{\infty} (\Delta P_{tie}^2 + \Delta f_1^2) dt \tag{6}$$

$$J_2 = \int_0^\infty t \left(|\Delta P_{tie}| + |\Delta f_1| \right) dt \tag{7}$$

To compute the optimum controller gains, a unit-step load change is assumed is area 1.

4. PSO RESULTS AND SIMULATION

In the first part of the study, a conventional AGC, which is only integral is considered. The initial runs were made with the bias constant $B = D + \frac{1}{R}$ [4]. Table 1 shows the optimum value for the integral gain and the relevant value of both objective functions.

Table 1. Optimum value of K_I [B = 0.425]

| | ISE | ITAE |
|--------------------|-------|-------|
| K_I | 0.669 | 0.453 |
| Objective function | 8.528 | 0.335 |

The effect of varying the frequency bias was studied next. Table 2 shows the optimum value for the integral gain K_I , the frequency bias constant *B* and the corresponding values of both objective functions.

Table 2. Optimum value of K_I and B

| | ISE | ITAE |
|--------------------|-------|--------|
| K_I | 0.545 | 0.607 |
| В | 0.559 | 0.28 |
| Objective function | 8.509 | 34.579 |

The proportional-plus-integral controller was considered next. Tables 3 and 4 tabulate the optimum values of the parameters and the corresponding values of the objective functions.

Table 3. Optimum value of K_I and K_{PR} [B = 0.425]

| | ISE | ITAE |
|--------------------|-------|--------|
| K_I | 0.447 | 0.49 |
| K_{PR} | 0.683 | -0.036 |
| Objective function | 6.316 | 36.937 |

Table 4. Optimum value of K_I , B and K_{PR}

| | ISE | ITAE |
|--------------------|-------|--------|
| K_I | 0.235 | 0.333 |
| K_{PR} | 0.589 | 0.507 |
| В | 3.334 | 1.975 |
| Objective function | 1.898 | 26.557 |

The dynamic responses for ΔP_{tie1} and Δf_1 corresponding to Table 3 and Table 4 are shown in Figures 2 and 3 respectively.



Figure 2a. Tie-line power deviation corresponding to Table 3.



Figure 2b. Frequency deviation corresponding to Table 3.



Figure 3a. Tie-line power deviation corresponding to Table 4.



Figure 3b. Frequency deviation corresponding to Table 4.

It is clear that for the ITAE case represented by the objective function J_2 , the damping of the oscillations is much improved and the transient error in both the frequency and the tie-line power is reduced when compared to the ISE case represented by the objective function J_1 .

5. CONCLUSION

Particle swarm optimization has been succesfully applied to tune the parameters of automatic generation control systems of the integral and the integral-plus-proportional type. A two-area reheat thermal system was assumed to demonstrate the method. The integral square of the error (ISE) and the integral of time-multiplied absolute value of the error (ITAE) were used as objective functions. The superiority of the ITAE in the damping and settling of the transient responses was demonstrated.

6. ACKNOWLEDGMENT

The authors acknowledge the support and encouragement of King Fahd University of Petroleum & Minerals.

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