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ON THE OPTIMAL LOAD FREQUENCY CONTROL OF AN INTERCONNECTED HYDRO ELECTRIC POWER SYSTEM USING GENETIC ALGORITHMS

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ABSTRACT
This paper deals with the application of genetic algorithms for optimizing the parameters needed for conventional automatic generation control (AGC) applied to interconnected hydro power systems. A two-area hydro power system is considered to exemplify the optimum parameter search. Digital simulations are performed aided by the integrated Simulink/Matlab environment in conjunction with the genetic optimization process. Several integral performance indices, or cost functions, are considered in the search for the optimal AGC parameters. The work utilize a more elaborate feedback control strategy, such as the proportional-plus-integral-plus-derivative type, within the decentralized frame. The results reported in this paper have not been obtained before and they demonstrate the effectiveness of the genetic algorithms in the tuning of such a process.

KEY WORDS
Load frequency control, AGC, hydro-power systems, genetic algorithms, Simulink/Matlab

1. Introduction

Many investigations have been reported in the past pertaining to AGC of a large interconnected power system with different types of units (steam, hydro, diesel) with either conventional or computational intelligence techniques, i.e. [1-5]. A net interchange tie-line bias control strategy has also 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 ACE 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]. 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 step-load change should vanish and also 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 and (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 controllers' gains and the frequency bias. The optimum parameter values of the classical AGC have been obtained in the literature (using integral or proportional-plus-integral) by minimizing the popular integral of the squared errors criterion (ISE) [1],[4]. This criterion has been used because of the ease of computing the integral both analytically and experimentally. A characteristic of the ISE criterion is that it weights large errors heavily and small errors lightly and it is not very selective. A system designed by this criterion tends to show a rapid decrease in a large initial error. Hence the response is fast, oscillatory and the system has poor relative stability [6].

In this work, we investigate the optimum adjustment of the load frequency controllers used in an interconnected hydro-power system, with the aim of genetic algorithms [7], and also, a set of performance indices which are various functions of error and time [8]. In this way, someone can observe the various performances that such a kind of power system might have when a different performance index is used. It should be noted that to the extent of the authors' knowledge, this kind of optimization has not been done in the literature. Finally, it is envisaged that the synthesis procedure highlighted in this paper could be of practical significance for tuning classical AGC parameters for an interconnected hydro-electric power system.

2. Genetic Algorithms

Genetic algorithms (GAs) are global search techniques, based on the operations observed in natural selection and genetics [9]. They operate on a population of current approximations – the individuals – initially drawn at random, from which improvement is sought. Individuals are encoded as strings (chromosomes) constructed over some particular alphabet, e.g. the binary alphabet {0,1}, so that chromosome values are uniquely mapped onto the decision variable domain. Once the decision variable domain representation of the current population is calculated, individual performance is assumed according to the objective function which characterizes the problem to use the variable parameters directly to represent the chromosomes in the GA solution. At the reproduction stage, a fitness value is derived from the raw individual performance measure given by the objective function, and used to bias the selection process. Highly fit individuals will have increasing opportunities to pass on genetically important material to successive generations. In this way, the genetic algorithms search from many points in the search space at once and yet continually narrow the focus of the search to the areas of the observed best performance. The selected individuals are then modified through the application of genetic operators, in order to obtain the next generation. Genetic operators manipulate the characters (genes) that constitute the chromosomes directly, following the assumption that certain genes code, on average, for fitter individuals than other genes. Genetic operators can be divided into three main categories [10], reproduction, crossover, and mutation. Reproduction selects the fittest individuals in the current population to be used in generating the next population. Crossover causes pairs, or larger groups of individuals to exchange genetic information within one another. Mutation causes individual genetic representations to be changed according to some probabilistic rule. GAs are more likely to converge to global optima than conventional optimization techniques, since they search from a population of points, and are based on probabilistic transition rules. Conventional optimization techniques are ordinarily based on deterministic hill-climbing methods, which, by definition, will only find local optima. GAs can also tolerate discontinuities and noisy function evaluations.

3. Load Frequency Control Problem

3.1. Power System Model and Control Strategy

The load frequency control (LFC) system investigated here, is composed of an interconnection of a two area hydro power system. The nominal parameters of the system are given in the Appendix. Fig. 1 shows the transfer function block diagram of a two-area small perturbation model of an interconnected hydro power system. The dynamic behaviour of the LFC system is described by the linear vector differential equation

$$\begin{aligned}\dot{\mathbf{X}} &= \mathbf{AX} + \mathbf{BU} + \mathbf{\Gamma P} \\ \mathbf{Y} &= \mathbf{CX}\end{aligned} \tag{1}$$

where **X**, **U** and **P** are the state, control and disturbance vectors respectively and **A**, **B** and **Γ** are real constant matrices of appropriate dimensions. According to Fig. 1, the state, control and disturbance vectors are defined as

$$\begin{aligned}\mathbf{X} = [\Delta f_{h1} \quad \Delta Pg_{h1} \quad \Delta Xg_{h1} \quad \Delta Xgh_{h1} \quad \Delta f_{h2} \quad \Delta Pg_{h2} \\ \Delta Xg_{h2} \quad \Delta Xgh_{h2} \quad \Delta P_{tie} \quad \textstyle\int ACE_{h1}dt \quad \int ACE_{h2}dt]^T\end{aligned} \tag{2}$$

$$\mathbf{U} = [u_1 \quad u_2]^T = [\Delta Pc_{h1} \quad \Delta Pc_{h2}]^T \tag{3}$$

$$\mathbf{P} = [Pd_1 \quad Pd_2]^T = [\Delta Pd_{h1} \quad \Delta Pd_{h2}]^T \tag{4}$$

With respect to both Fig. 1 and the Appendix, ΔPg_h is the incremental generation change, ΔPXg_h is the incremental governor water valve position change, ΔP_d is the incremental load demand change, Δf is the incremental frequency deviation, ΔP_{tie} is the incremental change in tie-line power, ΔPc_h is the incremental change in speed changer position, f is the nominal system frequency, H is the inertia constant, D is the load frequency constant ($Kps_h=1/D$, $Tps_h=2H/Df$), T_{12} is the synchronizing coefficient ($T_{12}=P_{h(max)}\cos(\delta_1-\delta_2)/Pr_h$), R is the speed regulation parameter, Tg_h is the governor time constant, T_h is the turbine time constant and T_w is the water time constant. The area control error (ACE) for the i^{th} area is defined as

$$ACE_h^i(t) = e^i(t) = \Delta P_{tie}^i(t) + B_i \Delta f_{hi}(t) \tag{5}$$

where B_i is the frequency bias constant. The conventional automatic generation controller found in literature has a linear integral only control strategy of the form

$$u_i = -K_I^i \int e^i(t)\,dt \tag{6}$$

In this work, for achieving the basic objectives of LFC, i.e., zero steady-state error in frequency and tie-line power, the discrete type PID controller is used (taken from Simulink/Matlab library) which is shown in Fig. 2. In this case, the control law for the i^{th} area (i=1,2) is

$$u_i = -K_P^i e^i(t) - K_I^i \int e^i(t)\,dt - K_D^i\left(\frac{de^i(t)}{dt}\right) \tag{7}$$

which when implemented in the Simulink/Matlab environment takes the form

$$u_i = -K_P^i e^i(kTs) - K_I^i \sum_0^{Tsim} e^i(kTs)\Delta t - K_D^i\left(\frac{\Delta e^i(kTs)}{\Delta t}\right) \tag{8}$$

where K_I^i, K_P^i and K_D^i are the gains of the PID controllers, Ts is the sampling time, $Tsim$ is the total simulation time and k=1,2,..,$Tsim/Ts$. In this study, the optimum values of the "K" parameters and B_i which minimize a whole set of different performance indices, are easily and accurately computed using a genetic algorithm. In a typical run of the GA, an initial population is referred to as the 0^{th} generation. Each individual in the initial population has an associated performance index value. Using the performance index information, the GA then produces a new population. The application of a GA involves repetitively performing two steps: (a) the calculation of the performance index for each of the individuals in the

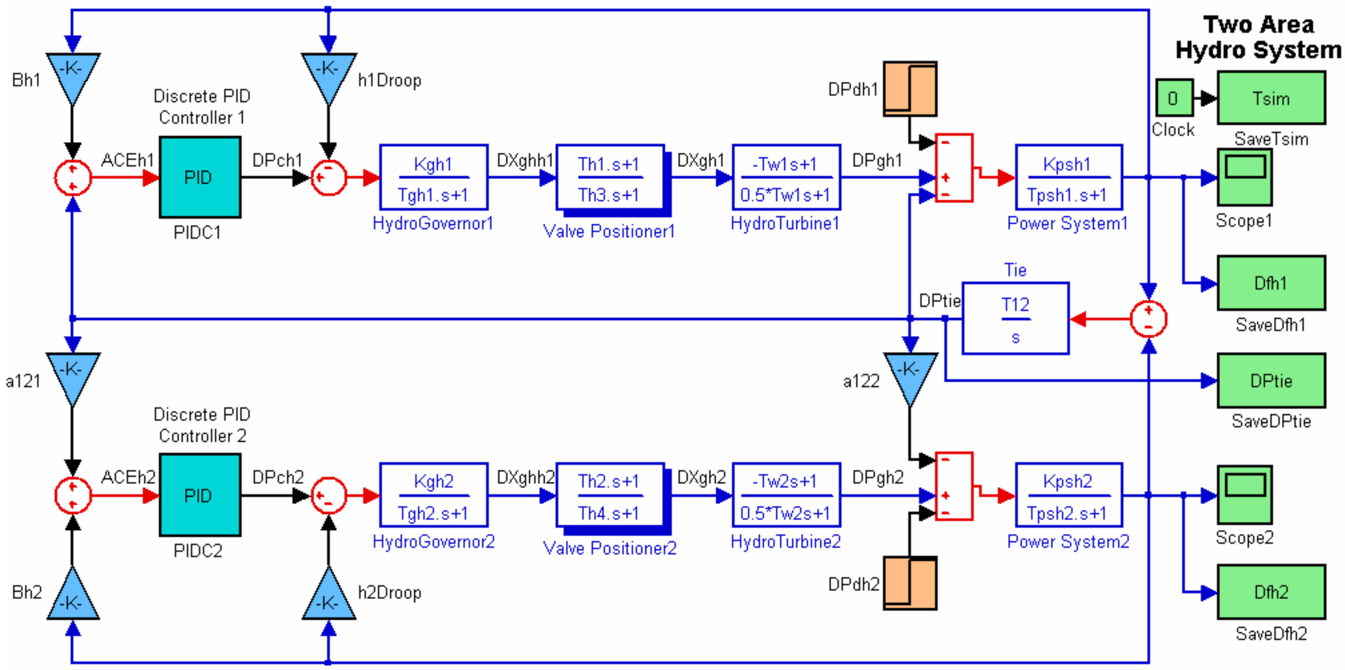

Fig. 1. *Transfer function model of a two area hydro power system implemented in Matlab/Simulink environment.*

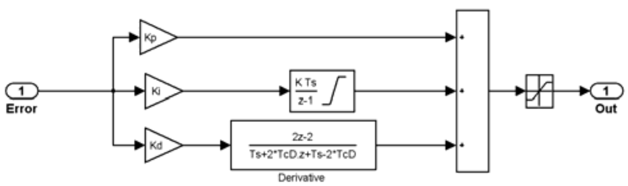

Fig. 2. *Matlab/Simulink used model for discrete type PID controller.*

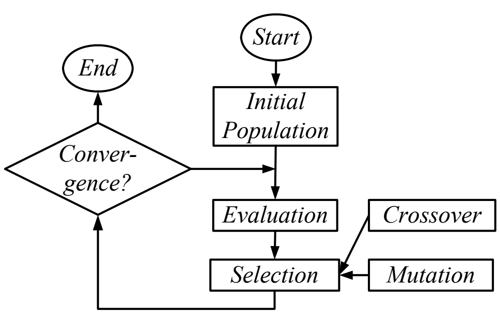

Fig. 3. *Simplified flowchart of a typical GA.*

current population. To do this, the system must be simulated to obtain the value of the performance index, (b) the GA then produces the next generation of individuals using the reproduction, crossover and mutation operators. These two steps are repeated from generation to generation until the population has converged, producing the optimum parameters. A flowchart of the GA optimization procedure is given in Fig. 3.

3.2. Performance Indices under Consideration

As it was aforementioned, in this work, we investigate the optimum adjustment of the load frequency controllers used in an interconnected hydro-power system, with the aim of genetic algorithms guided by a set of performance indices which are various functions of error and time. These indices include:

(a) The integral of the square of the error criterion (ISE) which is given by:

$$ISE = \int_0^\infty e^2(t)\,dt \tag{9}$$

(b) The integral of time-multiplied absolute value of the error criterion (ITAE) which is given by:

$$ITAE = \int_0^\infty t\left|e(t)\right|\,dt \tag{10}$$

This criterion penalizes long duration transients and is much more selective than the ISE. A system designed by use of this criterion exhibits small overshoot and well damped oscillations.

(c) The integral of time-multiplied square of the error criterion (ITSE) which is given by:

$$ITSE = \int_0^\infty te^2(t)\,dt \tag{11}$$

This criterion weights large initial error lightly, while errors occurring late in the transient response are penalized heavily. This criterion has a better selectivity than the ISE.

(d) The integral of squared time-multiplied absolute value of the error criterion (ISTAE) which is given by:

$$ISTAE = \int_0^\infty t^2\left|e(t)\right|\,dt \tag{12}$$

(e) The integral of squared time-multiplied square of the error criterion (ISTSE) which is given by:

$$ISTSE = \int_0^\infty t^2e^2(t)\,dt \tag{13}$$

Even though performance indices (c) through (e) have not been applied to any great extend in practice due to the increased difficulty in handling them, they are considered here. When the hydro-power system model (Fig. 1) is taken into account and also a discrete time control is performed, eqs. (9)-(13), are then translated into the following forms respectively

$$J_1 = ISE = \sum_{0}^{Tsim} \left(\Delta P_{tie}^2 + \alpha \Delta f_1^2 + \beta \Delta f_2^2 \right) \Delta t \qquad (14)$$

$$J_2 = ITAE = \sum_{0}^{Tsim} t \left(\left| \Delta P_{tie} \right| + \alpha \left| \Delta f_1 \right| + \beta \left| \Delta f_2 \right| \right) \Delta t \qquad (15)$$

$$J_3 = ITSE = \sum_{0}^{Tsim} t \left(\Delta P_{tie}^2 + \alpha \Delta f_1^2 + \beta \Delta f_2^2 \right) \Delta t \qquad (16)$$

$$J_4 = ISTAE = \sum_{0}^{Tsim} t^2 \left(\left| \Delta P_{tie} \right| + \alpha \left| \Delta f_1 \right| + \beta \left| \Delta f_2 \right| \right) \Delta t \qquad (17)$$

$$J_5 = ISTSE = \sum_{0}^{Tsim} t^2 \left(\Delta P_{tie}^2 + \alpha \Delta f_1^2 + \beta \Delta f_2^2 \right) \Delta t \qquad (18)$$

where J_m (m=1..5) is the objective function as described in Section 2, and α, β are penalty coefficients. To compute the optimum parameter values, a unit step load change is assumed in area 1 and the performance index is minimized using the GA. In the next Section, the optimum values of the parameters K_P^i, K_I^i, K_D^i and B_i resulting from minimizing the five different performance indices are presented. Two cases for each performance index were considered:

Case 1: α=0.065, β=0.0 (only frequency deviations in area 1 are penalized) and,

Case 2: $\alpha=\beta$=0.065 (frequency deviations in both areas are equally penalized).

4. Simulation and GA Results

To calculate the performance index, digital simulations of the system were performed over a solution time period (*Tsim*) of 120sec, for each of the individuals of any current population. The values of the performance indices thus obtained, were fed to the GA in order to produce the next generation of individuals. The procedure is repeated until the population has converged to some minimum value of the performance index producing near optimal parameters set. The GA used here utilizes direct manipulation of the parameters. The following GA parameters were used in the present research: Population size=60, maximum number of generations=40, Crossover probability=1.0, mutation probability=0.005. The particular choices of these parameters are generally problem dependent. However the GA performs best with a relatively high crossover probability, small mutation probability and a moderate population [9].

For each case study, two sub-cases were examined. First, the bias constant B was set to a value currently used by the industry, i.e. $B=D+1/R$. The optimum settings for the parameters K_P^i, K_I^i, K_D^i previously unavailable in the literature (except for the ISE performance index found in [11]), were obtained using the GA. Tables 1 and 2 summarize these values for all the performance indices

Table 1. *Optimum values of controllers' gains (α=0.065, β=0.0)*

	ISE	ITAE	ITSE	ISTAE	ISTSE
K_P	0.48240	0.19745	0.05610	0.01421	0.04269
K_I	-0.05818	-0.12029	-0.08984	-0.27820	-0.14652
K_D	-2.15543	-1.55056	-1.48861	-1.45385	-1.39700
J	0.0127	0.0079	0.0063	0.0101	0.0070

Table 2. *Optimum values of controllers' gains ($\alpha=\beta$=0.065)*

	ISE	ITAE	ITSE	ISTAE	ISTSE
K_P	0.04435	0.07361	0.05565	0.09422	0.07132
K_I	-0.08173	-0.17408	-0.09666	-0.11207	-0.11535
K_D	-1.48366	-1.35337	-1.62909	-1.45302	-1.42011
J	0.0063	0.0079	0.0065	0.0068	0.0067

Table 3. *Sub-optimum values of controllers' gains ($\alpha=\beta$=0.065) found in [11]*

	ISE
K_P	0.31775
K_I	0.01260
K_D	-0.43530
J	0.0195

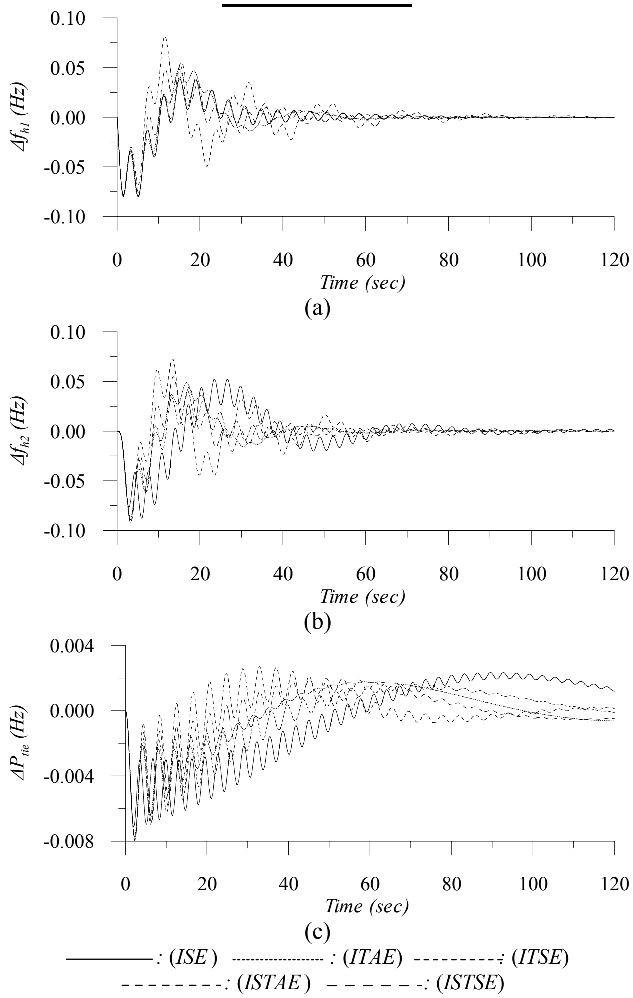

Fig. 4. *Time responses for Case 1: (a) Δf_{h1},(b) Δf_{h2}, (c) ΔP_{tie} . (fixed $B=D+1/R$)*

considered. Table 3 shows the optimum corresponding values found in [11]. From Table 2 (equal penalization of the frequency deviations) and Table 3, it is clear that the

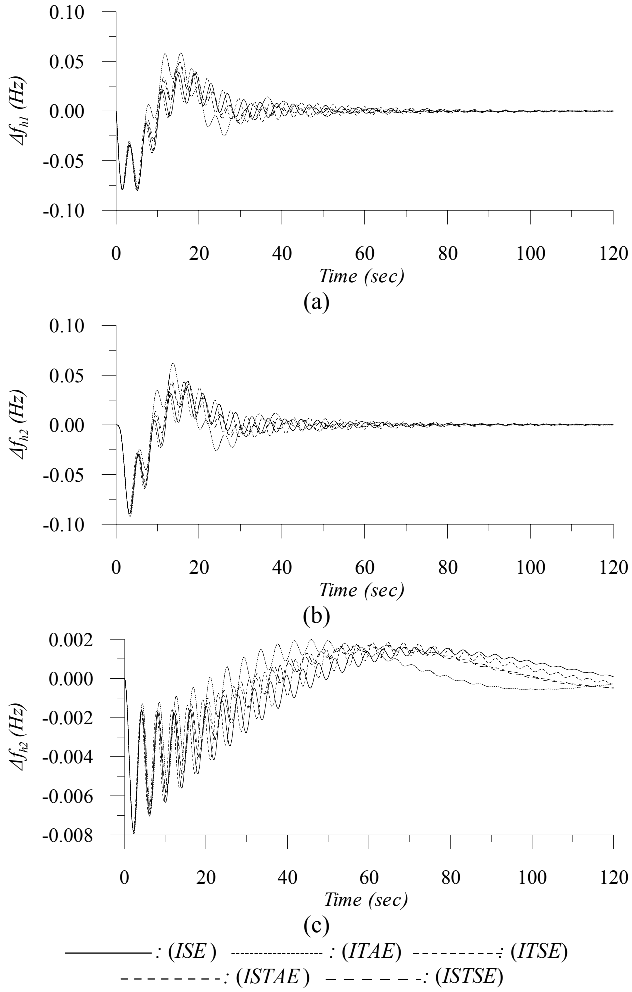

Fig. 5. *Time responses for Case 2: (a) Δf_{h1},(b) Δf_{h2}, (c) ΔP_{tie} . (fixed B=D+1/R)*

controllers' gains values proposed here, provide (even for the same performance index –ISE) better response.

The dynamic performances for Δf_{h1}, Δf_{h2} and ΔP_{tie} corresponding to Table 1 are displayed in Fig. 4, .while the dynamic performances corresponding to Table 2 are displayed in Fig. 5.

The responses obtained when the parameters are set according to the ITSE (in Case 1) indicate that the damping of oscillation is much improved and the transient error in both the frequency and the tie-line power is also much reduced. The same is observed for Case 2 when the parameters are set according to the ISE.

If the bias constant B is not fixed at a prescribed value, then the same technique could be used to obtain the optimal value of the parameters K_P^i, K_I^i, K_D^i and B_i, previously unavailable in the literature, for all performance indices. Tables 4 and 5 sum up these values for all the performance indices considered. Note that the value of all the performance indices considered has appreciably increased, compared to the case where the bias constant was held constant at the industry-chosen value. The optimum values of the bias constant, for all performance indices considered, suggest a bias setting which is less than the natural area characteristic.

Table 4. *Optimum values of controllers' gains and frequency bias (α=0.065, β=0.0)*

	ISE	ITAE	ITSE	ISTAE	ISTSE
K_P	1.17873	0.35307	0.52924	0.52589	1.13704
K_I	-0.09122	-1.96036	-0.10139	-1.68106	-1.42591
K_D	-1.63755	2.39781	-1.86385	2.35748	1.50780
B	0.14986	0.00591	0.26062	0.01317	0.00900
J	0.0165	0.0096	0.0110	0.0106	0.0095

Table 5. *Optimum values of controllers' gains and frequency bias (α=β=0.065)*

	ISE	ITAE	ITSE	ISTAE	ISTSE
K_P	1.24019	0.75652	1.02507	0.76881	0.70238
K_I	-1.40077	-1.35408	-1.29400	-1.35702	-1.48958
K_D	0.32824	2.19150	1.82613	2.25226	3.02556
B	0.01426	0.01975	0.00595	0.02335	0.00698
J	0.0103	0.0117	0.0092	0.0130	0.0094

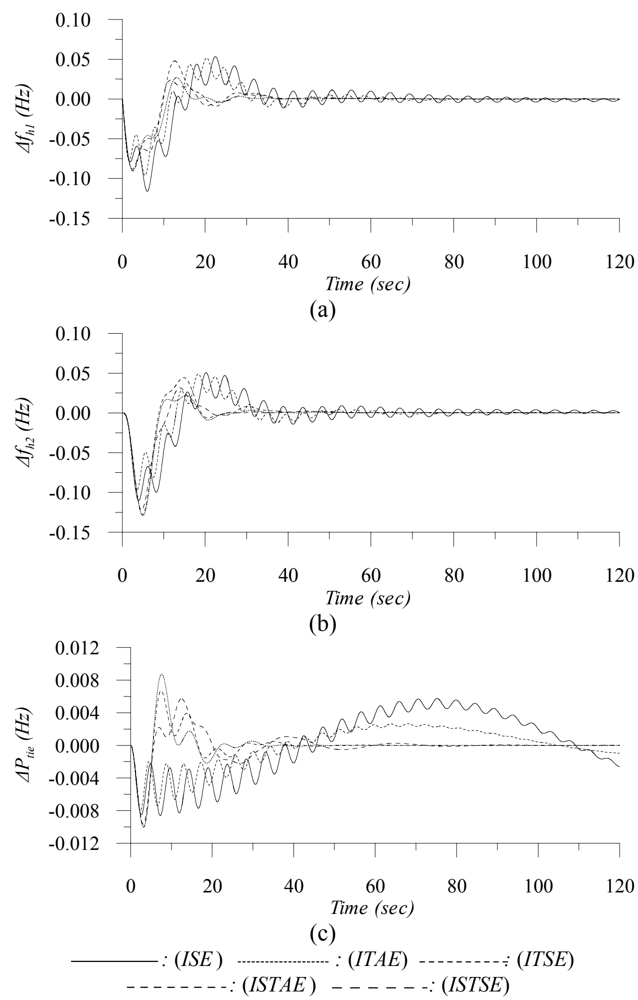

Fig. 6. *Time responses for Case 1: (a) Δf_{h1},(b) Δf_{h2}, (c) ΔP_{tie} . (B=not fixed)*

The dynamic performances for Δf_{h1}, Δf_{h2} and ΔP_{tie} corresponding to Table 4 are displayed in Fig. 6. while the dynamic performances corresponding to Table 5 are displayed in Fig. 7. The superiority of the responses obtained when the control parameters are set based on minimizing the ISTSE is clearly demonstrated for Case 1,

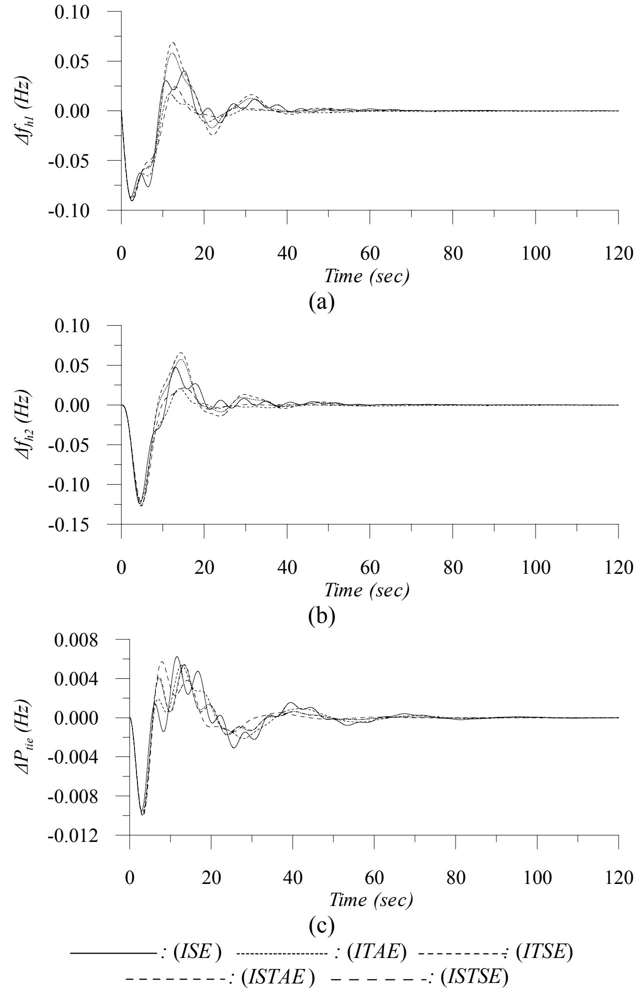

Fig. 7. *Time responses for Case 2: (a) Δf_{h1},(b) Δf_{h2}, (c) ΔP_{tie} . (B=not fixed)*

while for Case 2 the minimization of the ITSE (once again) gives better results.

5. Conclusion

In this paper, a new method of tuning the parameters of conventional automatic generation control systems of the proportional plus integral plus derivative type is described. A two-area hydro system is assumed to demonstrate the method. Several performance indices are considered. These include in addition to the popular integral square of the error (ISE), the integral of time-multiplied absolute value of the error (ITAE), the integral of time-multiplied square of the error (ITSE), the integral of squared time-multiplied absolute value of the error (ISTAE), and the integral of squared time-multiplied square of the error (ISTSE). For each performance index, a digital simulation of the system is carried out and optimization of the parameters of the AGC systems is achieved in a simple and elegant manner through the effective application of genetic algorithms. It is clear that the dynamic performance of the system, using the optimal parameters, is resulting from the minimization of a different performance index (and not only the ISE currently used in literature). In this way, the lack of poor damping and settling time (relative to the other indices), as well as the improvement of the transient error in both the frequency and tie-line power, can be assured. Also, the results obtained indicate the superiority of the PID strategy over the integral or the proportional-plus-integral ones (not shown here). Further work will examine, how the optimal parameters of the load frequency controllers are influenced due to the variations of the water starting time constant (*Tw*), the inertia constant (*H*), as well as, the behaviour of such a kind of power system when it operates under a deregulated electricity market environment.

Appendix

Data for Hydro Power System

f_o=50Hz, $Pr_{h1}=Pr_{h2}$=2000MW, $P_h^{(max)}$=200MW,
$Tg_{h1}=Tg_{h2}$=5s, $T_{h1}=T_{h2}$=48.7s, $T_{h3}=T_{h4}$=5s, $T_{w1}=T_{w2}$=1s,
$Kg_{h1}=Kg_{h2}$=1, $M_{h1}=M_{h2}=Tp_{h1}/Kp_{h1}=2H_{h1}/f_o$=0.167puMW-s^2,
$D_{h1}=D_{h2}=1/Kp_{h1}$=0.00833puMW/Hz, δ_1-δ_2=30^o,
$R_{h1}=R_{h2}$=2.4Hz/puMW, $B_{h1}=B_{h2}$=0.425puMW/Hz,
$\Delta Pd_{h1}=\Delta Pd_{h2}$=0.01puMW, 2π$T_{12}$=0.545puMW.

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