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Hybrid GA-SA Based Optimal AGC of a Multi-Area Interconnected Power System

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Abstract: The Automatic Generation Control (AGC) of interconnected power systems has been considered as one of the most challenging problems for about the last four decades. Following the pioneering research of Elgerd and Fosha in 1970, a heap of research are appeared from time to time on optimal AGC of power systems considering various structural as well as technical aspects of power systems. This study is an attempt to propose a design of optimal AGC gains of a multi-area power system. The design of optimal AGC gains is based on Genetic Algorithm (GA) and Simulated Annealing (SA). It is a synergetic combination of GA and SA through a penalty function. The penalty function is derived based on the transient response specifications of dynamic response of the interconnected power system. A multi-area interconnected power system model is considered for the investigations. The power system model consists of three identical control areas consisting of reheat thermal plants. The investigations have been carried out with the designed Automatic Generation Controllers (AGC) based on GA-SA considering 2% load perturbation in one of the areas. The system dynamic responses obtained for various system states are compared with those achieved using optimal controllers derived using Linear Quadratic Regulator (LQR) theory. The simulation results show that the proposed GA-SA based optimal load frequency controllers are superior in all respects in comparison to the optimal AGC based on LQR theory.

Key words: Automatic generation control, genetic algorithm, simulated annealing, linear quadratic regulator, multi-area power system, area control error

INTRODUCTION

Due to numerous technical and economical reasons, the interconnections between individual utilities and areas as well have increased. The size and capacity of the power systems have been enlarged and with the strengthening of interconnections, abnormal phenomena have been frequent observed such as excessively large tie-line power deviations and/or sustained power oscillations under sudden system load changes. This fact suggests the necessity of more advanced control strategies to be incorporated for better control. Therefore, the efforts are always on to make the operation and control of the interconnected power systems more reliable, economic and cost effective. Intelligent systems based on computers have been employed for on-line monitoring and control of modern large-scale power systems in generation, transmission and distribution, thereby overcoming the complexities and drawbacks of the conventional control schemes. The design of system controllers based on the classical control theory in general do not yields optimal system performance where as the controller design using optimal control theory and its optimization makes the system control more meaningful in the sense of its optimality (Elgerd, 1982; Abdennour, 2002; Kothari *et al*., 1989; Huddar and Kulkarni, 2009; Ibraheem and Kothari, 2005). The optimal AGC regulators based on Linear Quadratic Regulator (LQR) design technique have been found to offer very promising results in comparison to those AGC regulators designed using classical control schemes. However, optimal AGC regulators are considered to be impractical due to the reasons (Mathur and Ghosh, 2006). Still they have been preferred for the applications against the AGC regulators based on classical control concepts.

The recent advancement in optimal control theory and availability of high speed digital computers coupled with enormous capability of handling large amount of data motivated the power system engineers/researchers to devise advanced AGC strategies. It is the fact that every physical system is pervasively imprecise, uncertain and hard to be categorical about. It is also a fact that precision and certainty carry a cost. To deal such systems effectively and most efficiently, a flexible approach called evolutionary algorithms has emerged on research scenario and has been very widely in use over the last two decades. One of the newer and relatively simple approaches used for optimization is GA. Besides other merits, it has a very important quality of being derivative free optimization technique. Therefore, it does not require a detailed model of the system to be optimized. It becomes desirable to consider the optimal AGC regulator design

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based on linear full state feedback control concept and GAs. The power engineers and researchers have considered the GA as an intelligent tool to design optimal AGC regulators due to its inherent features to get global minima for an optimization problem (Abdel-Magid and Dawoud, 1996; Aditya and Das, 2003; Daneshfar and Bevrani, 2009; Chidambaram and Paramasivam, 2009). The limitations of the GA-based method, however are that it is difficult to obtain a high quality solution because the GAs lack in fine local tuning capabilities and it also takes a large computation cost (Yip and Pao, 1995). In this study, researchers present a hybrid approach to overcome the limitations and also propose to hybridize the Simulated Annealing (SA) which is based on a local searching algorithm to compensate the fine local tuning capabilities of GA. The hybrid GA-SA technique yields more optimal gain values than the GA method (Ghoshal, 2004). The optimal automatic generation controller designs based on the approach reported for power system applications have been reported in the literature. In the present research, the hybrid form of genetic algorithm and simulated annealing techniques is proposed for better control in the multi-area power system. These techniques included system frequency and power flow deviations as a variable parameter for the new controller. The GA-SA based controller gives good transient response, insensitivity to parameter variations and external disturbances.

The effect of parameter variations on system dynamic performance has been tested comprehensively. The significant advantages of the proposed method over the optimality (LQR) theory include the following direct representation of constraints on transient response specifications treatment of constraints as hard constraintsability to handle non-linear, time varying systems also. The controller is tested on a multi-area i.e., three equal area thermal power system with reheats turbines with AC tie-lines for this test case. A comparison of test results with those from LQR method shows that the proposed controller performs better than the LQR theory based controller. The LFC design based on the LQR based strategy does not offer good system dynamic performance in the wake of 2% load perturbations in the one of the area interconnected power systems.

MATERIALS AND METHODS

System investigated: The power system transfer function model is shown in Fig. 1 and the state equations of the power system are written in time domain as:

$$\frac{d}{dt}(X) = A\underline{X} + B\,\underline{U} + \Gamma\underline{Pd} \qquad (1)$$

$$\underline{Y} = C\underline{X} \qquad (2)$$

The structure of vectors X, U and $\underline{P_d}$ may be developed as follows: The structure of the state, control and disturbance vectors are shown as:

$$[\underline{X}] = \begin{bmatrix} \int\Delta ACE_1 & \Delta Xg_1 & \Delta Pr_1 & \Delta Pg_1 & \Delta F_1 & \Delta Ptie_1 \\ \int\Delta ACE_2 & \Delta Xg_2 & \Delta Pr_2 & \Delta Pg_2 & \Delta F_2 & \Delta Ptie_2 \\ \int\Delta ACE_3 & \Delta Xg_3 & \Delta Pr_3 & \Delta Pg_3 & \Delta F_3 & \Delta Ptie_3 \end{bmatrix}^T$$

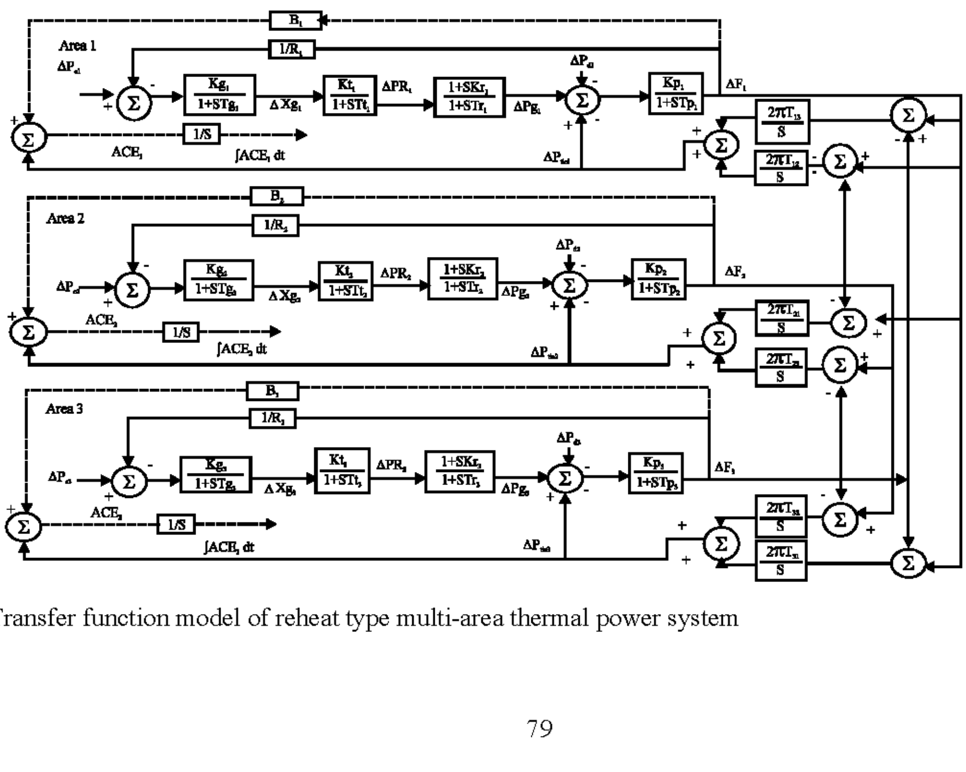

Fig. 1: Transfer function model of reheat type multi-area thermal power system

$$\left[\underline{U}\right] = \left[\Delta Pc_1, \Delta Pc_2, \Delta Pc_3\right]^T$$

$$\left[\underline{P}_d\right] = \left[\Delta Pd_1, \Delta Pd_2, \Delta Pd_3\right]^T$$

System matrices: The system matrices, A, B and Γ described by Eq. 1 and 2 can be obtained with the structures of state, control and disturbance vectors and the transfer function block diagram representation of Fig. 1. The selection of power system configuration is done based on the development trend of electricity power scenario in India. It is assumed that for economic, technical and other reasons the power systems will continue to operate in interconnected fashion. However, the future structure of power systems may have larger geographical boundaries all over the country.

The corresponding coefficient matrices are derived using the numerical values of system variables as given in Appendix. System model and these matrices are obtained as follows:

$$A=\begin{bmatrix}
0&0&0&0&0.43&1&0&0&0&0&0&0&0&0&0&0&0&0\\
0&-12.5&0&0&-5.21&0&0&0&0&0&0&0&0&0&0&0&0&0\\
0&0.6&-0.1&0&0&0&0&0&0&0&0&0&0&0&0&0&0&0\\
0&0&3.33&-3.33&0&0&0&0&0&0&0&0&0&0&0&0&0&0\\
0&0&0&6.0&-0.05&-6.0&0&0&0&0&0&0&0&0&0&0&0&0\\
0&0&0&0&1.08&0&0&0&0&0&-0.54&0&0&0&0&0&-0.54&0\\
0&0&0&0&0&0&0&0&0&0&0.43&1&0&0&0&0&0&0\\
0&0&0&0&0&0&0&-12.5&0&0&-5.21&0&0&0&0&0&0&0\\
0&0&0&0&0&0&0&0.60&-0.1&0&0&0&0&0&0&0&0&0\\
0&0&0&0&0&0&0&0&3.33&-3.33&0&0&0&0&0&0&0&0\\
0&0&0&0&0&0&0&0&0&6.0&-0.05&-6&0&0&0&0&0&0\\
0&0&0&0&-0.54&0&0&0&0&0&1.08&0&0&0&0&0&-0.54&0\\
0&0&0&0&0&0&0&0&0&0&0&0&0&0&0&0&0.43&1\\
0&0&0&0&0&0&0&0&0&0&0&0&0&-12.5&0&0&-5.21&0\\
0&0&0&0&0&0&0&0&0&0&0&0&0&0.60&-0.1&0&0&0\\
0&0&0&0&0&0&0&0&0&0&0&0&0&0&3.33&-3.33&0&0\\
0&0&0&0&0&0&0&0&0&0&0&0&0&0&0&6.0&-0.05&-6.0\\
0&0&0&0&-0.49&0&0&0&0&0&-0.49&0&0&0&0&0&0.99&0
\end{bmatrix}$$

$$B^T=\begin{bmatrix}
0&12.5&0&0&0&0&0&0&0&0&0&0&0&0&0&0&0&0\\
0&0&0&0&0&0&0&12.5&0&0&0&0&0&0&0&0&0&0\\
0&0&0&0&0&0&0&0&0&0&0&0&0&12.5&0&0&0&0
\end{bmatrix}$$

$$\Gamma^T=\begin{bmatrix}
0&0&0&0&-6&0&0&0&0&0&0&0&0&0&0&0&0&0\\
0&0&0&0&0&0&0&0&0&0&-6&0&0&0&0&0&0&0\\
0&0&0&0&0&0&0&0&0&0&0&0&0&0&0&0&-6&0
\end{bmatrix}$$

The state cost weighting matrix Q and control cost weighting matrix R have been selected as an identity matrix of compatible dimensions, respectively.

The hybrid GA-SA technique: The hybrid GA-SA based controller is designed by Hybrid Stochastic Search (HSS) Technique (Deb, 2005). The HSS heuristic incorporates Simulated Annealing (SA) in the selection process of Evolutionary Programming (EP) (Das and Patvardhan, 2002). The solution string comprises of all feedback gains and is encoded as a string of real numbers. The population structure of HSS is shown in Table 1.

Table 1: Population structure of HSS

Family 1	Family 2	Family 3	…….	Family n
Parent 1	Parent 2	Parent 3	…….	Parent n
Child 11	Child 21	Child 31	…….	Child n1
Child12	Child 22	Child 32	…….	Child n2
-	-	-	……	-
-	-	-	…….	-
-	-	-	……	-
Child 1w	Child 2x	Child 3y	……	Child nz

The HSS heuristic employs blend crossover and a mutation operator suitable for real number representation to provide it a better search capability. The objective is to minimize the Area Control Error (ACE) augmented with penalty terms corresponding to transient response specifications in the controller output, frequency and power flows in the transmission lines. The heuristic is quite general and various aspects like nonlinear, discontinuous functions and constraints are easily incorporated as per requirement. The heuristic can be easily understood from the following pseudo-code:

- Initialize T^1 and T^{MAXIT}, N parent strings, M
- For each parent i, generate m (i) children using crossover
- Employ the mutation operator with probability Pm
- Find the best child for each parent (Ist level of competition)
- Select the best child as the parent for the next generation

For each family, accept the best child as the parent for next generation if:

$$Y_1 < Y_2 \text{ or } \exp((Y_2 - Y_1)/T) \geq \rho$$

Where:

Y_1 = The objective value of the best child
Y_2 = The objective value of its parent
T = The temperature coefficient
ρ = A random number uniformly distributed between 0 and 1

- Repeat step 7-10 for each family count = 0
- Repeat step 9 for each child; Goto step 10
- Increase count by 1, if:

$$((Y_1 < Y_2) \text{ or } \exp((Y_{LOWEST} + Y_1)/T) \geq \rho)$$

Where:

Y_1 = The objective value of the child
Y_2 = The objective value of the parent

Y_{LOWEST} = The lowest objective value ever found
T = The current temperature
ρ = A random number uniformly distributed between 0 and 1

- Acceptance number of the family is equal to count (A)
- Sum up the acceptance numbers of all the families (S)
- For each family i, calculate the number of children to be generated in the next generation according to the following formula:

$$m\ (i) = \frac{(C x A)}{S}$$

where, C is the children generated by all the families.

- Decrease the temperature
- Repeat step 2-13 until a certain number of iterations have been completed

A briefly detailed explanation of each step is as follows: this study presents the implementation details for HGASA application. The solution string comprises of all feedback gains. A real string representation is chosen. Population size of 100 is chosen as a compromise between exhaustive search and computational burden. Following are the implementation details of the algorithm:

Crossover: For each parent i, mates are selected from the other parents at random and crossover is applied to generate m (i) children. To start with, m (i) is fixed same for all the parents. This number is changed as the search progresses as explained in the subsequent steps. The Blend Crossover operator (BLX-α) based on the theory of interval schemata is employed in this study. BLX-α operates by randomly selecting a point in the range (p1-α (p2-p1), p2 + α (p2-p1)) where p1 and p2 are the two parent points and p1<p2. In the test problem, BLX-0.5 performed better than the BLX operators with any other α value and has therefore been used.

Fitness evaluation: The objective here is to minimize the deviation in the frequency of the three areas and the deviation in the transmission line power flows. The fitness function is taken as the summation of the absolute values of the three at every discrete time instant in the simulation. An optional penalty term is added to take care of the transient response specifications viz. transient response specifications on system frequency, power flows, settling time, over shoots, etc.

Selection: The best child (the child with minimum objective value) out of the children generated from the same parent is found. The best child then competes with its parent to survive in the next generation. If the best child is better than it's parent, it is accepted as a parent in the next generation. If the best child is worse than it's parent then there is the Boltzmann criterion that the child be accepted as described.

The selection process is inspired from the SA mechanism and allows a bad move to be selected in the optimization process with a probability. This is in contrast to the conventional evolutionary algorithms where only good moves are accepted throughout the optimization process which may cause the algorithm to get stuck in local minima.

Boltzmann criterion: As in SA, the selection of temperatures is such that initially the probability of acceptance of a bad move i.e., accepting the best child as the parent for next generation when it is worse than the current parent is high (approximately 1) but as the temperatures are successively lowered this probability is decreased till at the end, the probability of accepting a bad move is negligible (approximately 0). Such a strategy enables the technique to seek the global optimum without getting stuck in any local optimum (Das and Patvardhan, 2002).

The initial and final temperatures are calculated as follows: A bad move is accepted according to the Boltzmann Criterion. Initially, the probability of accepting a bad move is approximately one, i.e.,

$$\exp\left(\frac{-\Delta X_{average}}{T^1}\right) = 0.99$$

and finally,

$$\exp\left(\frac{-\Delta X_{average}}{T^{MAXIT}}\right) = 0.0001$$

therefore,

$$T^1 = \frac{-\Delta X_{average}}{\log\ (0.99)}$$

$$T^{MAXIT} = \frac{-\Delta X_{average}}{\log\ (0.0001)}$$

Where:
T^1 = Initial temperature
T^{MAXIT} = Final temperature
$\Delta x_{average}$ = Average difference between the objective X for any two neighborhood points in the search space. This average is calculated over a number of chromosomes

Cooling schedule: Temperature is cooled down with the iterations as under:

$$T^{k+1} = \frac{T^k}{(1+ \beta x T^k)}$$

Where:

$$\beta = \frac{(T^1 - T^{MAXIT})}{(T^1 x T^{MAXIT} x(MAXIT-1))}$$

where superscript k represents the iteration count.

Acceptance number: The number of children generated in the next generation is proportional to a parameter called the acceptance number. This number provides a measure of the goodness of the solutions in the vicinity of the current parent. The number is computed by sampling the search space around the current parent and counting the number of good samples out of the total samples as per step 7-10 of the pseudo-code. This strategy enables the algorithm to focus search on the better regions of the search space.

RESULTS AND DISCUSSION

Computational exeperience: The investigation has been performed on MATLAB 7.4 version computing system. The case study-wise optimal feedback gain matrices is computed and is shown in Table 2. The response plots for various state variables are obtained for 2% load disturbance in $area_1$. These response plots are shown in Fig. 2-10.

The results obtained have been compared with those from LQR theory an optimal control algorithm. The test case assumes 2% load disturbance in $area_1$. Figure 2-7 show the dynamic response of frequency deviations (ΔF_1-ΔF_3) changes in the power generations (ΔPg_1-ΔPg_3) and Fig. 8-10 presents area control errors deviations ($\int ACE_1$-$\int ACE_3$) with optimal controller and the proposed optimal state feedback controller (GA-SA). Response of LQR is sluggish and associated with large number of oscillations, large settling time and large magnitudes of overshoots when load disturbance is 2% is considered in $area_1$. The settling time of Hybrid GA-SA algorithm is approximately <6 sec. However, improvement with the system is about 50%.

Comparison of this method with LQR theory shows that inspite of its wider applicability the search power of the heuristic is immense and it succeeds in finding better solutions than the existing method for any case. The comparison shows that the proposed controller gives better performance than the conventional optimal control.

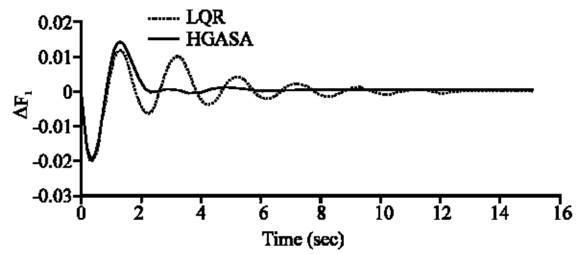

Fig. 2: Response of ΔF_1 for 2% load perturbation in $area_1$

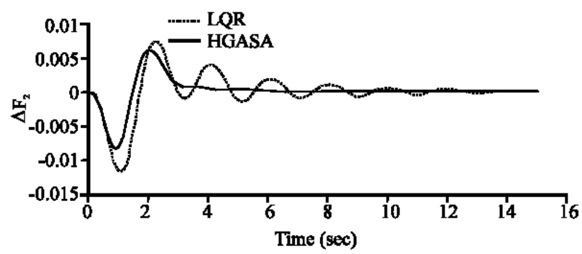

Fig.3: Response of ΔF_2 for 2% load perturbation in $area_1$

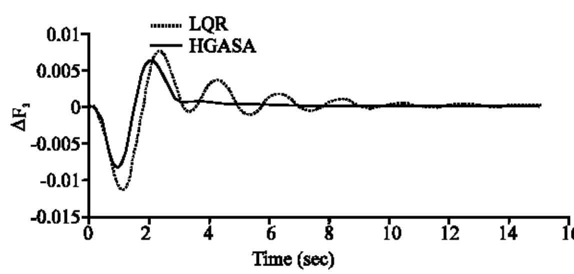

Fig. 4: Response of ΔF_3 for 2% load perturbation in $area_1$

Table 2: Optimal State Feedback gains for LQR and HGASA based Regulators

Optimal all State Feedback Gain Matrices for LQR (K)

1	0.5692	4.8218	1.2331	0.0034	-3.0905	-0.0000	0.0158	0.5194	0.3926	0.055
-0.7445	-0.0009	0.0176	0.5833	0.4495	0.5355	-0.9319	-	-	-	-
-0	0.0158	0.5194	0.3926	0.5055	-0.7445	1.0000	0.5692	4.8218	1.2331	0.0034
-3.0905	-0.0009	0.0176	0.5833	0.4495	0.5355	-0.8319	-	-	-	-
0.0009	-0.7752	1.0000	0.5761	0.4062	0.4993	-0.7752	0.0009	0.0176	0.5761	0.4062
0.4993	-0.7752	1.0000	0.5756	5.0318	1.3618	0.0956	-3.3522	-	-	-

Optimal all State Feedback Gain Matrices for GA-SA (K)

0.4073	0.4536	0.7605	2.6203	-0.0138	0.0664	-0.1978	0.4823	-0.135	1.5527
0.5037	1.4592	0.1967	0.5762	-0.4356	0.7413	0.4271	2.3986	-	-
-0.0739	0.2525	-0.2563	0.2519	0.7703	1.1376	0.2961	0.4952	1.6563	1.4301
0.0375	-0.0100	-0.0048	-0.4693	1.4133	0.4787	0.3000	0.3256	-	-
0.2151	0.4933	0.4755	0.5360	0.4954	0.8072	-0.3069	-1.2244	1.2113	0.4567
0.8076	0.3746	0.0081	1.0553	0.9511	0.8501	-0.7145	0.2359	-	-

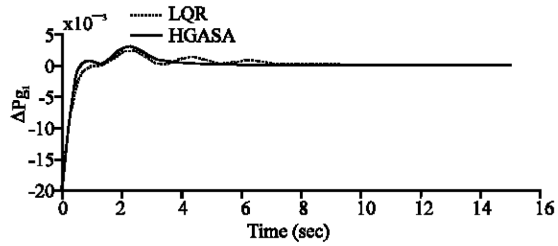

Fig. 5: Response of Δ Pg_1 for 2% load perturbation in $area_1$

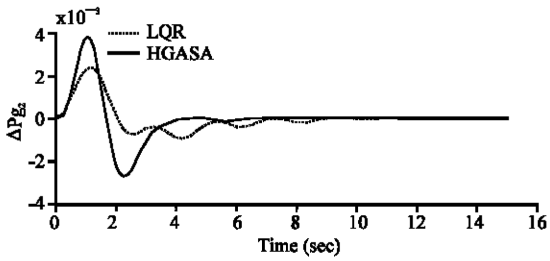

Fig. 6: Response of Δ Pg_2 for 2% load perturbation in $area_1$

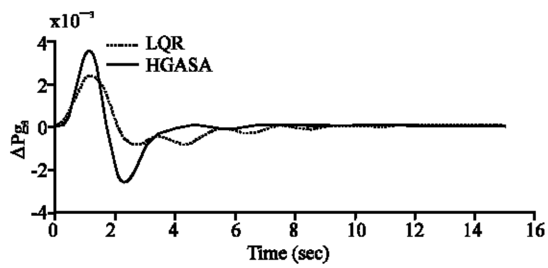

Fig. 7: Response of Δ Pg_3 for 2% load perturbation in $area_1$

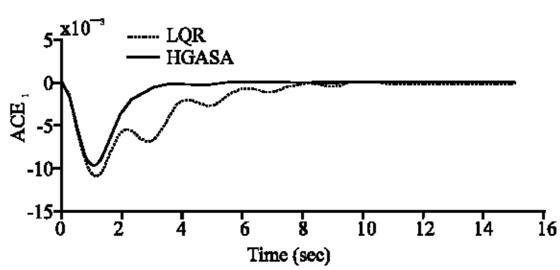

Fig. 8: Response of $\int ACE_1$ for 2% load perturbation in $area_1$

For the case, the parameters of HSS are kept same and are given:

Number of parents (N) = 10
Number of children (NC) = 100
Maximum number of iterations (MAXIT) = 50
Probability of crossover = 0.6
Probability of mutation = 0.01

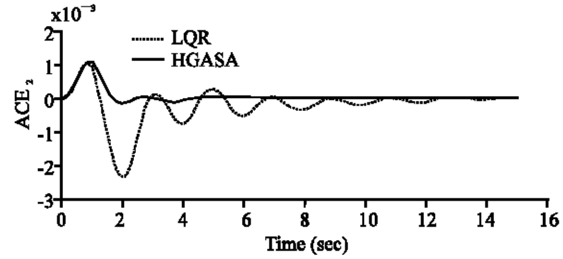

Fig. 9: Response of $\int ACE_2$ for 2% load perturbation in $area_1$

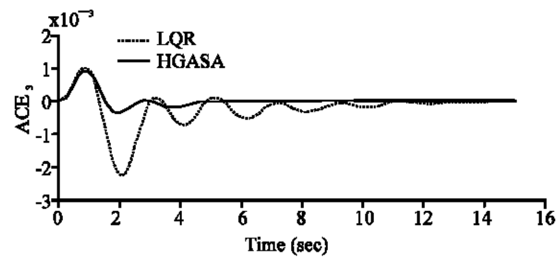

Fig. 10: Response of $\int ACE_3$ for 2% load perturbation in $area_1$

CONCLUSION

A new Hybrid GA-SA approach has been proposed for optimizing the state feedback gains for AGC in this study. A penalty function based technique is used for handling the constraints imposed on the transient response of the system. Test results presented on a multi-area power system with an A.C. link and are compared with those obtained from an optimal controller based on Linear Quadratic Regulator theory. Test results describe the efficacy of the proposed approach in optimizing the state variable feedback gains to give a fairly better controller performance.

NOMENCLATURE

ΔF_i	=	Incremental change in frequency
i	=	Subscript referring to area (i = 1, 2 and 3)
ΔP_{gi}	=	Incremental change in generator power output
ΔP_{di}	=	Incremental change in load demand (p.u.MW/Hz)
Δx_{gi}	=	Incremental change in governor valve position
T_{pi}	=	Electric system time constants
R_i	=	Speed regulation parameter, Hz/p.u.MW
K_i	=	Integral gain constant
$\Delta P_{tie\,I}$	=	Incremental change in tie-line power (MW)
T_{gi}	=	Speed governor time constant of area 'i', s
K_{ri}, T_{ri}	=	Reheat coefficient's and reheat time's

B_i	=	Frequency bias constant (p.u.MW/Hz)
ACE_i	=	Area control error's
T_{ti}	=	Turbine time constants
A, B, C, Γ	=	System matrices of a dynamic model in state space form
Dp_{ci}	=	Incremental change in speed changer position
K_{gi}	=	Speed governor gain
Kti	=	Reheat thermal turbine gain constant
T_{12}, T_{13}	=	Synchronizing coefficient of ac tie-link of area (i)
$\underline{X}$, $\underline{U}$, $\underline{Y}$, $\underline{P_d}$	=	State, control, output and disturbance vector of a model in state space form

APPENDIX

Nominal parameters of the system investigated: $B_1 = B_2 = B_3 = 0.425$, $R_1 = R_2 = R3 = 2.4$ Hz/ p.u. MW, $T_{g1} = T_{g2} = T_{g3} = 0.08$ sec, $K_{r1} = K_{r2} = K_{r3} = 0.5$ sec, $T_{r1} = T_{r2} = T_{r3} = 10$ sec, $T_{t1} = T_{t2} = T_{t3} = 0.3$ sec, $K_{p1} = K_{p2} = K_{p3} = 120$ Hz/ p.u. MW, $T_{p1} = T_{p2} = T_{p3} = 20$ sec, $a_{12} = -1$, $\Delta Pd_1 = 0.02$ p.u.MW, Nominal frequency = 50Hz, $2\pi T_{12} = 0.545$ p.u.MW .

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