Robust Design of Automatic Generation Controller by Genetic Algorithm

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Abstract — Frequency is a common factor throughout the system and is dependent on the active power balance. For normal and satisfactory operation of an interconnected system, it is essential to maintain constant frequency and tie-line power exchange. A turbine speed governor on each generating unit provides the primary speed control action hence controls small deviations of frequencies and large frequency deviations are effected by supplementary control originating at central control centre that allocates the generation. The control of generation and frequency is commonly referred to as load-frequency control (LFC). Since the system load demand is continuously changing, it is therefore necessary to change the power settings automatically. Hence automatic generation control (AGC), a supplementary controller is installed at selected generating units of a control area to maintain active power balance. The satisfactory operation of AGC requires robust optimal controller parameters that provide better dynamic performance over a wide range of operating conditions and various load scenarios. In the proposed work, robust design of proportional-integral-derivative (PID) controller using real coded genetic algorithm (GA) for a two area interconnected system is presented. An Eigen value based objective function is employed for this purpose. The effectiveness of GA is determined by comparing the results with conventional Ziegler-Nichols PID tuning method. The robustness analysis of GA based design through Eigen value analysis and dynamic simulations is demonstrated.

I. INTRODUCTION

An interconnected system comprises of several control areas interconnected by means of tie lines. A control area constitutes a coherent group so that the generators speed up and slow down together maintaining their relative power angles [1]. For normal and satisfactory operation of an interconnected system, it is essential to maintain constant frequency and tie-line power exchange [1]. Constant frequency ensures constancy of speed of induction and synchronous motor based drive systems. Generating units employ several auxiliary drives associated with the fuel, the feed water and combustion air supply units. Therefore, the overall satisfactory operation of a generating unit requires relatively close control of frequency. Moreover, in a transmission network, frequency reduction can lead to excessive magnetizing currents in transformers and induction motors.

The frequency is a common factor throughout the system and is dependent on the active power balance. Frequency deviation is a direct result of the imbalance between the electrical load and the power supplied by the connected generators, so it provides a useful index to indicate the generation and load imbalance. Since the frequency generated in the electric network is proportional to the rotation speed of the generator, the problem of frequency control may be directly translated into a speed control problem of the turbine generator unit. A turbine speed governor on each generating unit provides the primary speed control action, which allocates a portion of the total load demand based on its droop characteristics. On the other hand, a supplementary control originating at central control allocates the generation. The control of generation and frequency is commonly referred to as load-frequency control (LFC).

When the speed changer setting of primary speed control is fixed, the generating unit will operate under free-governor operation mode. Under free-governor operating mode, any change in load demand is balanced by stored kinetic energy in the generator rotor with corresponding change in frequency deviation. When the load demand increases, the stored kinetic energy in the rotating masses will be released by reduction of frequency so as to match the increased load demand. On the other hand, when the load demand decreases, excessive energy will be transferred to rotating masses thus increasing the stored kinetic energy and frequency. The steady-state frequency deviation following a change in load demand by ΔP_d in a control area is given as

$$\Delta f = \frac{K_{ps} R}{K_{ps} + R}\left(\Delta \mathrm{P}_c - \Delta \mathrm{P}_d\right) \qquad (1)$$

where, Kps =gain of power system area, R =speed regulation of the governor or droop and ΔP_c =change in power setting. From (1), it is clear that with free-governor operation $(\Delta P_c = 0)$, a change in load demand always results in corresponding change in steady-state frequency of operation. However, these steady-state frequency deviations following a change in load demand ΔP_d can be eliminated by effecting a corresponding change in set point, ΔP_c. That is with $\Delta P_c = \Delta P_d$, Δf tends to zero.

Under normal operation, the small frequency deviations can be attenuated by the primary control. For larger frequency deviation (off-normal operation), according to the available amount of power reserve, the supplementary controller or Automatic Generation Controller(AGC) is responsible for restoring system frequency. However, for a serious load-generation imbalance associated with rapid frequency changes following a significant fault, the AGC system may be unable to restore frequency via the supplementary frequency control loop. In this situation, the emergency control and protection schemes, such as under-frequency load shedding (UFLS), must be used to decrease the risk of cascade faults, additional generation events, load/network, and separation events [2].

It is quite evident from the foregoing discussions that under off-normal operation restoration of frequency to nominal value requires supplementary control action to adjust the load reference set-point. Therefore, the basic means of controlling prime-mover power to match variations in system load in a desired manner is through control of load power reference of selected generating units. Since the system load demand is continuously changing, it is therefore necessary to change the power settings automatically.

Automatic generation control (AGC) is a supplementary controller installed at selected generating units of an area provides an effective mechanism for adjusting the generation to minimize frequency deviation and regulate tie-line power flows. The AGC system is used to maintain the active power balance by the adjustment of set points. Thus, the main objectives of AGC are to keep the system frequency at the scheduled value, and regulate the generator units based primarily on area control error (ACE), making the area control error tends to zero under the continuous adjustment of active power, so that the generation of entire system and load power well match [2].

The AGC analysis and synthesis has been augmented with valuable research contributions during the last two decades. Significant improvements have appeared in the area of AGC designs to cope with uncertainties, various load characteristics, changing structure, and integration of new systems, such as energy storage devices, wind turbines, photovoltaic cells, and other sources of electrical energy. Numerous analog and digital control schemes using nonlinear and linear optimal/robust, adaptive, and intelligent control techniques have been presented. The most recent advance in the AGC synthesis to tackle the difficulty of using complex/nonlinear power system models or insufficient knowledge about the system is the application of intelligent concepts such as neural networks, fuzzy logic, genetic algorithms, multi-agent systems, and evolutionary and heuristic optimization techniques which brought the concept of Intelligent AGC.

II. REAL CODED GENETIC ALGORITHM(GA)

Genetic algorithm (GA) is a numerical optimization algorithm that is capable of being applied to a wide range of optimization problems, guaranteeing the survival of the fittest. The genetic algorithm is developed by Holland.J.H in 1975. It imitates natural genetic process based on natural selection and genetics. Darwinian principle of ”survival of the fittest” and survive by adaptation in the competing world forms the basis for GA.

A. GA mechanism

The GA mechanism is inspired by the mechanism of natural selection, where stronger individuals would likely be the winners in a competing environment. GA begins with a set of initial random populations represented by chromosomes. Chromosomes are the structures that encode the prescriptions of the construction of an organism. In general chromosomes are the strings of defining genes. Normally in a genetic algorithm parameters to be optimized are represented in the form of strings of real numbers subjected to the constraints. These strings are considered as chromosomes. A simplified flowchart for GA is shown in Fig. 1.

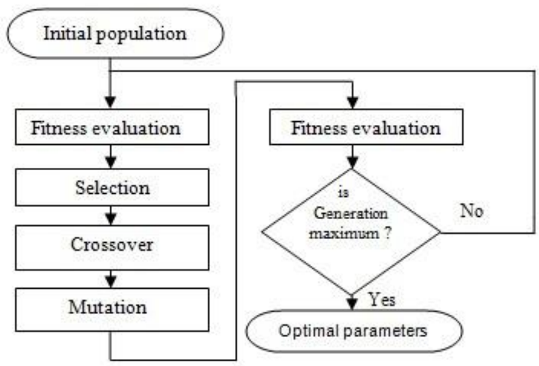

Fig. 1. A simplified GA flowchart

To start the optimization, GA uses randomly produced initial solutions. This method is preferred when a prior information about the problem is not available. There are basically three genetic operators used to produce a new generation: selection, crossover, and mutation. The GA employs these operators to converge at the global optimum. Considering the design variables to constitute a chromosome, operations involved in real coded genetic algorithm are summarized as follows [13].

1) Generation of initial population: In the real coding representation, each chromosome is encoded as a vector of floating point numbers, with the same length as the vector of decision variables. The real coding representation is accurate and efficient because it is closest to the real design space and the string length is the number of variables to be optimized.

A chromosome is represented as a vector $(x_1, x_2, ...x_i, ...x_N)$ to represent a solution to the optimization problem. Initialization process produces M chromosomes, where M denotes the population size, by the following algorithm.

Algorithm

a) Generate an array (M×N) of random numbers.

b) Considering each random number in a row as β mapping is done using $x_i = l_i + \beta(u_i - l_i)$, where l_i and u_i are the domain of x_i. Repeat N (number of genes) times and produce a vector $(x_1, x_2, ...x_i, ...x_N)$.

c) Repeat the above steps M times and produce M initial populations.

2) Selection: Selection/reproduction operator performs survival of the fittest and hence carries only fit chromosomes from the initial population into new population. Different selection methods such as roulett-wheel, expected number control or ranking-based selection can be used. Expected number control and roulett-wheel selection methods are probability based. Combination of ranking based selection and expected number control based selection method increases the accuracy. Selection considers objective function and fitness value to determine the performance of a chromosome.

a) Objective functions: are the performance requirements of a problem.

Example: error, minimum, maximum value.

b) Fitness function: Performance index of GA to resolve the viability of each chromosome.

In the present investigation ranking and expected number control methods are employed.

Expected number control: Steps involved in the method are summarized as below. [2]

1) Considering M as the number of chromosomes average fitness is given by

Average population fitness = $$(fit)_{av} = \frac{\sum fit_i}{M} \quad (2)$$

2) Relative average fitness of i^{th} chromosome is given by

$$(fit_{r,av}) = \frac{fit_i}{(fit)_{av}} \quad (3)$$

3) The chromosomes with a higher relative average fitness have a higher chance to be selected for later breeding. The number of copies of i^{th} chromosome represented by x_i is determined by relative average fitness by neglecting the decimal part.

The above steps are repeated until the total number of copies of chromosomes become equal to the size of initial population

M. Each chromosome is represented according to the number of copies in the resulting population. The population resulted from selection acts as parent population for crossover and mutation operators.

3) Crossover: Crossover is a recombination operator. It involves random exchange of gene information between two randomly selected high-fit chromosomes from the parent population. The crossover operator works on pairs of selected solutions with a certain crossover rate. The crossover rate is defined as the probability of applying a crossover to a pair of selected solutions (chromosomes). There are many ways to define the crossover operator. The most common way is the one-point crossover.

The crossover operators used here are the one-cut-point crossovers which randomly selects one cut-point, exchanges the right parts of two parents after the cut point, and calculates the linear combinations at the cut-point genes to generate new offspring.

Let two parents be $x = (x_1, x_2, ...x_N)$ and $y = (y_1, y_2, ...y_N)$, where N is number of genes. If they are crossed after the k^{th} position, the resulting off-springs are

$$x' = (x_1, x_{2,} .....x'_k, y_{k+1}, y_{k+2}, ..., y_N) \quad (4)$$

$$y' = (y_1, y_{2,} .....y'_k, x_{k+1}, x_{k+2}, ..., x_N) \quad (5)$$

Where $x'_k = x_k + \beta(y_k - x_k)$, $y'_k = l_k + \beta(u_k - l_k)$, where l_k and u_k are the domain of y_k, and β is a random value, such that $\beta \in \{0, 0.1, 0.2, ...,1\}$.

4) Mutation: Mutation is an occasional random alteration of a real value at a string position of a low-fit Chromosome based on the mutation probability. Mutation probability is generally set to be small. The mutation operator helps to prevent destructive crossover. It prevents the GA from being trapped in a local minimum.

In real coded genetic algorithm two genes in single chromosome are randomly chosen to execute the mutation. The method is designed to enhance the fine tuning capabilities. For a given $x = (x_1, x_2, ..., x_i, x_j, x_k, ...x_N)$, if the elements x_i and x_k are randomly selected for mutation, the resulting offspring is $x' = (x_1, x_2, ..., x'_i, x_j, x'_k, ...x_N)$ The two new genes x'_i and x'_k are

$$x'_i = (1-\beta)x_i + x_k\beta \qquad (6)$$

$$x'_k = (1-\beta)x_k + x_i\beta \qquad (7)$$

Hence, the information generated by the fitness evaluation unit about the quality of different chromosomes is used by the selection operation in the GA. Selection operation generates parent population. The probabilities assigned to the crossover and mutation specify the number of the children. Best fit M chromosomes from the set of initial parent population, off-springs generated by crossover and mutation are chosen for next generation parent population for the optimization process. The algorithm is repeated until a predefined number of generations is reached. Optimal chromosome at the end of maximum generation with optimum fitness represents the optimal values of design variables.

III. PROBLEM FORMULATION

A. Two area LFC model

A two-area interconnected system consists of two identical control areas connected by a single tie line. The transfer function AGC model of two-area power system is given in Fig. 2.

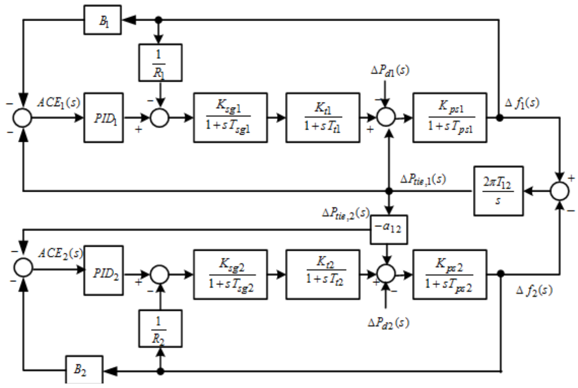

Fig. 2. Transfer function AGC model.

Considering both frequency and tie-line power deviations of i^{th} control area, the area control error ACE_i can be written as

$$ACE_i(s) = -B_i \Delta f_i(s) - \Delta P_{tie,i}(s) \qquad (8)$$

The control objective is to regulate the area control error at zero under steady state conditions, which implies zero steady state error in both frequency and tie-line deviations. In order that the area control errors of two-areas be made zero, a PID controller must be introduced in the two areas.

The PID controller is the most popular feedback controller used in the process industries. It is a robust, easily understood controller that can provide excellent control performance despite the varied dynamic characteristics of process plant. As the name suggests, the PID controller consists of three basic modes, the proportional mode, the integral and the derivative modes. A proportional controller has the effect of reducing the rise time, but never eliminates the steady-state error. An integral control has the effect of eliminating the steady-state error, but it may make the transient response worse. A derivative control has the effect of increasing the stability of the system, reducing the overshoot, and improving the transient response. Hence use of proportional-integral derivative controller improves the performance of automatic generation controller. PID controller is a robust controller that provides excellent performance irrespective of the varied conditions of the plant.

In the present study, non-interactive PID controllers with low pass filters are implemented. With filter coefficient N the transfer function of i^{th} PID controller is given as

$$G_{ci}(s) = k_{pi} + \frac{k_{ii}}{s} + \frac{k_{di} N_s}{s + N} \qquad (9)$$

where filter coefficient N=10. The state space linear model of the system around an initial operating point is given as

$$\Delta \dot{X} = A \Delta X$$

where A is the state matrix and ΔX is the state vector.

B. Problem statement

In the AGC design for a two-area power system there are six parameters to be optimized. Objective function for the optimization of parameters is first defined based on the desired specifications and constraints. In the present study, an optimization objective based on Eigen value λ is employed.

The Eigen values of the system are determined by the A matrix by solving $|\lambda I - A| = 0$, where I is the identity matrix. The objective function J for optimization employing Eigen value λ is given as:

$$J = \max\left\{ \mathrm{Re}\,al(\lambda_i) + \beta + \left| \frac{1}{\alpha} \mathrm{Im}(\lambda_i) \right| \right\} \text{ for i=1,2,3..,n.} \quad (10)$$

If a solution is obtained such that $J < 0$, it will place all the closed loop Eigen values in a wedge shaped sector shown in Fig. 3. In the present study the fitness J of the Eigen value away from the wedge shape is selected for every chromosome and is minimized such that all the Eigen values are placed in the selected wedge shaped sector.

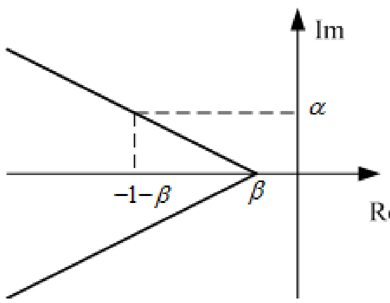

Fig. 3. Wedge shape sector in the complex plane

Thus the optimization problem can be stated as follows:

Determine PID parameters: $k_{p1}, k_{p2}, k_{i1}, k_{i2}, k_{d1}, k_{d2}$

So as to: Minimize J

Subject to constraints: $0.0001 < k_{pi}, k_{ii}, k_{di} < 3.0$

The above stated optimization problem is solved using GA. The robustness of the design is tested by Eigen value analysis and performance comparison of GA with Ziegler- Nichols conventional tuning method in terms of overshoot and settling times of transients.

IV. RESULTS AND DISCUSSIONS

A. Simulated Results

MATLAB based programs were developed to simulate AGC designs by hybrid genetic-Taguchi optimization procedure. The interconnected power system considered in the present study consisted of two identical areas. Ratings of each area is: Rated frequency (fr) =50 Hz. Rated capacity (Pr) =250 MW, Inertia constant (H) = 5 s, Regulation (R) = 3 Hz/MW, Nominal operating load (Pd) =125 MW. The nominal system parameters are detailed in Appendix. The effectiveness of Real coded genetic algorithm based design (denoted as GA-AGC), is evaluated by comparing its performance with PID tuned using conventional tuning technique based on Ziegler-Nichol's tuning method (denoted as ZN-AGC).

1) GA-AGC: The optimization of AGC parameters are performed using GA with following parameters: Number of chromosomes (Nc) = 200; Maximum number of generations (Ngmax) = 400; Probability of crossover (pc) = 0.8; Probability of mutation (pm) = 0.05. The fitness of the chromosomes are evaluated in terms of the objective function J with α=2 and β=0.25. The convergence of fitness function is depicted in Fig. 4. The final value of the best fitness was found to be around 0.0070 which indicates that all closed loop Eigen values have been shifted nearer to the chosen wedge shaped sector in the complex s-plane.

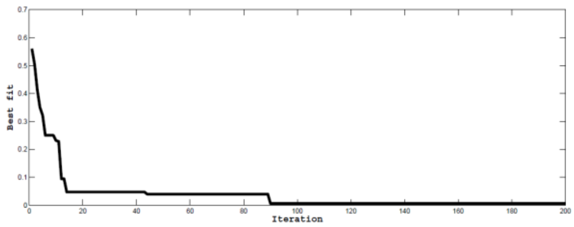

Fig. 4. Plot showing the convergence of GA-AGC

In order to evaluate the robustness of GA, simulations were performed 50 times with random initializations. Table I summarizes the frequency of attaining best fitness value within specific ranges out of 50 runs. It can be seen from the Table I that GA-AGC has provided 72% of times an optimal solution with the best fitness value lying in the range [0.0070 – 0.2070].

TABLE I.SUMMARY OF FREQUENCY OF CONVERGENCE OF GA-AGC

Range of best Fitness	Number of convergence	percentage of convergence
0.0070-0.0570	4	8
0.0571-0.1070	5	10
0.1071-0.1570	9	18
0.1571-0.2070	18	36
0.2071-0.2570	10	20
0.2571-0.3070	3	6
0.3071-0.3570	1	2
Total	50	100

2) ZN-AGC: A MATLAB-SIMULINK model of the nominal isolated area AGC system is developed for the design of ZN-AGC. The ultimate gain (Kcu) and ultimate period (Tu) are determined by setting only proportional mode of PID controller in AGC system. The identical PID parameters for two areas are calculated using values of Kcu and Tu according to the gain setup given in Appendix. Summary of the optimal PID parameters of GA-AGC and ZN-AGC are given in Table II.

TABLE II SUMMARY OF OPTIMAL PID PARAMETERS

Method	k_{p1}	k_{p2}	k_{i1}	k_{i2}	k_{d1}	k_{d2}
GA	0.176	0.192	0.5471	0.4398	0.4685	0.5569
ZN	0.568125	0.568125	0.6679	0.6679	0.309	0.309

B. Robustness Analysis

Robustness of GA-AGC is evaluated by:

1) Eigen value analysis

2) Dynamic simulations

1) Eigen value analysis: The closed loop Eigen values

of the two area AGC system under different loading conditions are calculated from the state space matrix using the optimal PID parameters of GA-AGC and ZN-AGC respectively. The loading conditions are functions of area gain (Kps) and time constant (Tps). Summary of closed loop Eigen values of the system under different loading conditions of GA-AGC and ZN-AGC are given in Tables III and IV respectively.

TABLE III. CLOSED LOOP EIGEN VALUES OF GA-AGC UNDER DIFFERENT LOAD CONDITIONS

heavy load condition (Kps = 50; Tps = 10)	light load condition (Kps = 100; Tps = 20)	low load condition (Kps = 150; Tps = 30)
-10.6654	-10.6627	-10.6618
-10.7728	-10.7697	-10.7687
-1.3235±j2.1214	-1.3077±j2.0940	-1.3025±j2.0847
-1.2311±j1.9434	-1.2074±j1.9138	-1.1995±j1.9035
-0.6141±j0.7167	-0.6210±j0.7381	-0.6236±j0.7461
-0.5887±j0.6099	-0.5762±j0.6399	-0.5716±j0.6494
-0.2469	-0.2430	-0.2418

TABLE IV. CLOSED LOOP EIGEN VALUES OF ZN-AGC UNDER DIFFERENT LOAD CONDITIONS

heavy load condition (Kps = 50; Tps = 10)	light load condition (Kps = 100; Tps = 20)	low load condition (Kps = 150; Tps = 30)
-10.4710	-10.4690	-10.4683
-10.4589+	-10.4569	-10.4563
-2.7631	-2.7618	-2.7614
-2.6650	-2.6642	-2.6640
-0.2895±j2.0367	-0.2607±j2.0295	-0.2511±j2.0270
-0.4161±j1.9014	-0.3873±j1.8918	-0.3777±j1.888
-0.6318	-0.6422	-0.6457
-0.5517	-0.5660	-0.5707
-0.2472	-0.2437	-0.2426

From comparison of closed loop Eigen values mentioned in Tables III and IV it can be seen that under heavy load condition the Eigen values drift towards higher damping region and under light loading condition the Eigen values drift towards lower damping region. By comparison of the Eigen values, it is observed that drift in the position of Eigen values is minimum in GA-AGC. Further, it is also observed that all the closed loop Eigen values have been shifted more nearer to the chosen wedge shaped sector in the complex s-plane using GA-AGC.

2) Dynamic simulations: Further, the robustness of GATAG-AGC design is evaluated by dynamic simulations. The dynamic performance of the designed AGC is tested using time domain simulations of the MATLAB SIMULINK model of the two area AGC system. In this simulation frequency deviations and tie line power deviations are monitored by applying a step load increase of 0.01 pu in area-1 using optimal PID parameters of GA-AGC and ZN-AGC under varying load conditions. The simulation results obtained are presented as below:

1) Frequency deviations of area 1 in Figs. 5-7.
2) Frequency deviations of area2 in Figs. 8-10.
3) Change in Ptie1 in Figs. 11-13.
4) Change in Ptie2 in Figs. 14-16.

From the time domain simulations it can be seen that the GA-AGC is highly satisfactory in terms of peak-overshoot and settling times over ZN-AGC. Also it is clear from the Figs. 5- 16 that GA-AGC is very effective in damping the oscillations of the system from heavy to low load conditions. This agrees with Eigen value based analysis.

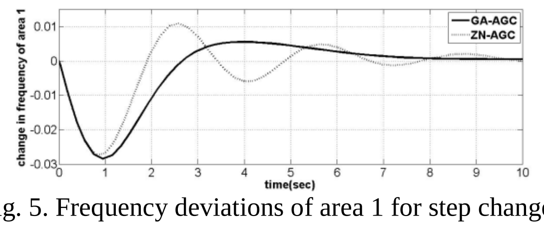

Fig. 5. Frequency deviations of area 1 for step change in load (heavy loading)

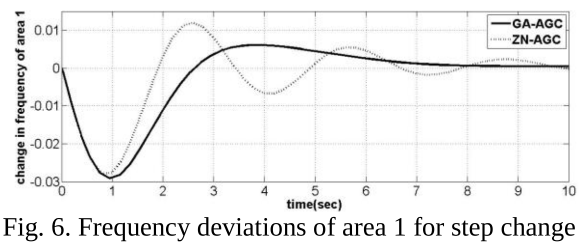

Fig. 6. Frequency deviations of area 1 for step change in load (nominal loading)

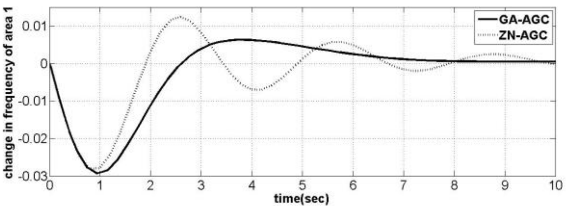

Fig. 7. frequency deviations of area 1 for step change in load (light loading)

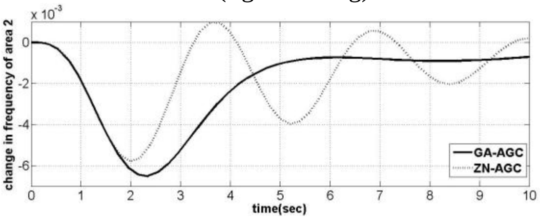

Fig. 8. Frequency deviations of area 2 for step change in load (heavy loading)

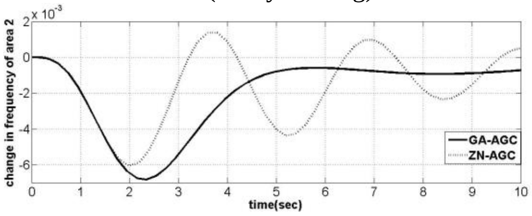

Fig. 9. Frequency deviations of area 2 for step change in load (nominal loading)

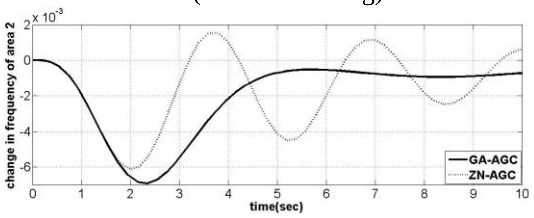

Fig. 10. Frequency deviations of area 2 for step change in load (light loading)

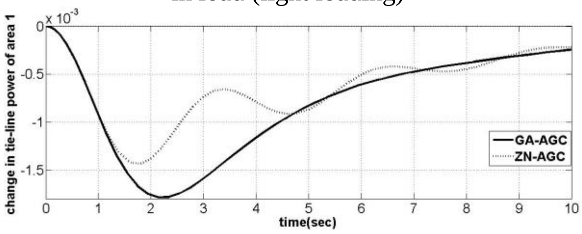

Fig. 11. Tie line power deviations of area 1 for step change in load (heavy loading)

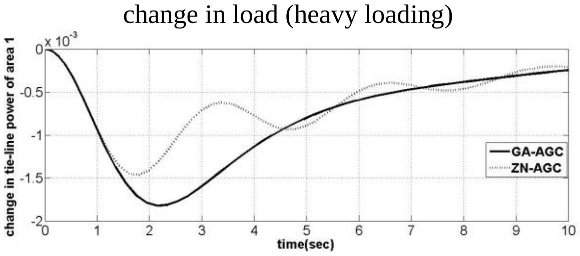

Fig. 12. Tie line power deviations of area 1 for step change in load (nominal loading)

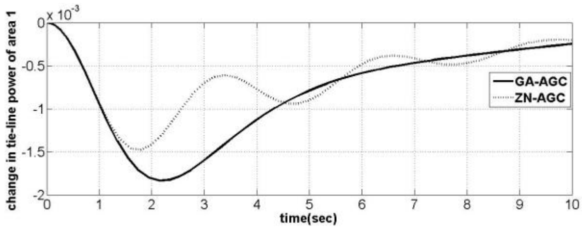

Fig. 13. Tie line power deviations of area 1 for step change in load (light loading)

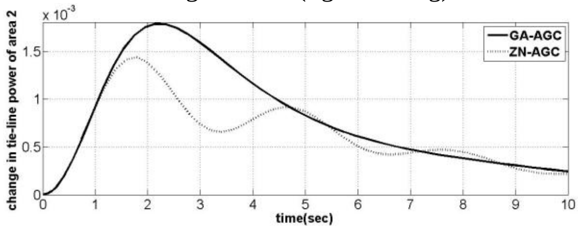

Fig. 14. Tie line power deviations of area 2 for step change in load (heavy loading)

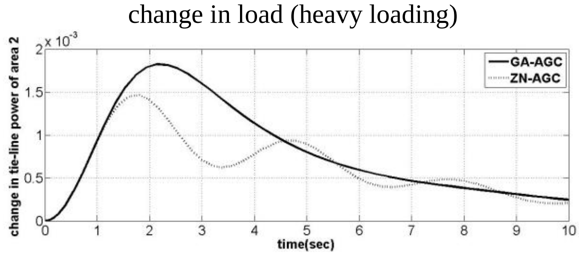

Fig. 15. Tie line power deviations of area 2 for step change in load (nominal loading)

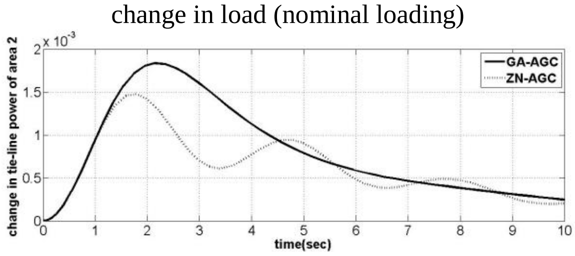

Fig. 16. Tie line power deviations of area 2 for step change in load (light loading)

CONCLUSION

The proposed work focuses on GA based optimization procedure. Application of GA for the robust AGC design for the two area power system is presented. The comparison based on Eigen value analysis and dynamic simulations under different loadings indicated that the performance of GA based AGC is superior and robust as compared to conventional based design.

APPENDIX

TABLE V. VALUES OF SYSTEM CONSTANTS

System constant	Value
Speed governor gains(Ksg1 = Ksg2)	1.0
Turbine gains(Kps1 = Kps2)	1.0
Speed regulations (R1 = R2)	3.0 Hz/MW
Turbine gains(Kt1 = Kt2)	1.0
Time constant of speed governor(Tsg1 = Tsg2)	0.4

Area gain(Kps1 = Kps2)	100
Time constant(Tps1 = Tps2)	20
Stiffness of tie line(T12)	0.00795
frequency bias(B1 = B2)	0.4
Filter coefficient(n)	10

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