DISTRIBUTED GENETIC ALGORITHMS BASED CONTROL METHOD FOR REDUCING STRUCTURAL RESPONSES UNDER SEISMIC EXCITATION

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ABSTRACT

Genetic Algorithms (GAs) have been used as an effective optimization search technique in various fields including the area of control design. This paper develops a new Distributed Genetic Algorithm (DGA) based optimal control method to reduce the structural response under seismic excitation. In DGA a large population is divided into smaller subpopulation and a traditional GA is executed on each subpopulation separately. The developed control method uses Kalman filter estimator technique to obtain the full state performance from the available reduced order feedback. Using this method, best performance is obtained for described controller. The controller is optimized using DGA without making simplifying assumption. DGA is used to solve the resulting constrained optimization problem with the nonlinearity of the cost function.

KEY WORDS

Active Control, Distributed Genetic Algorithms (DGA), Active Mass Driver (AMD), Benchmark Problem.

INTRODUCTION

In recent years considerable research activity has occurred in the area of active structural control for civil structures. Although significant progress has been made towards the design of feasible and practically realizable controllers for earthquake engineering applications, assessing the overall status of this research field has been difficult because of the relatively wide variability in control objectives. The benchmark problems presented by Spencer et al.(1997) attempt to enforce a specific set of objectives, thus providing a common ground from which various control design methods may be tested. This research employs total acceleration measurements of selected degrees of freedom as the feedback quantity for the controllers. Accelerometers are one of the most commonly employed sensors on civil structures in seismic zones, and direct use of accelerations requires no additional signal processing to obtain a relevant measurement for feedback. Acceleration feedback has been employed in civil structural control in several recent research efforts. Most optimization methods used in control design are traditional gradient based search methods .With this

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approach there are difficulties associated in selecting the suitable continuous differentiable cost function and in considering nonlinearities (Gray et al. 1995).Compared with the traditional gradient based search methods, Genetic Algorithms (GAs) efficiently find an optimal value from the complex and possibly discontinuous solution space because the fitness function is the only information required of the problem. GAs does not require reformulating the problem into a suitable form unlike traditional gradient based search techniques. As a result, GA's provides a lot of flexibility in the controller design and optimization. Genetic Algorithms in the field of control systems have considerable works but in the field of structural control we have very few works. In the field of structural control design, GAs have been used successfully to obtain gains for optimal controller(Kundu and Kawata 1996) , tune the weights of neuro–controllers (Lewis and Fagg 1992), and scale parameters of fuzzy controllers (Kim et al. 1995) obtain the gains from state space reconstruction (Kim and Ghaboussi, 1997).

For the control of the civil structures, we proposed a new Real-Coded Distributed Genetic Algorithms based control method. The proposed control method estimates the system states from the available reduced order feedback using the Kalman Filter technique and optimizes control gain by using DGA. The advantages of this method are the flexibility, simplicity and robustness.

EXPERIMENTAL STRUCTURE

The structure on which the evaluation model is based is an actively controlled, three-story, single-bay, model building considered in Dyke et al. (1995). The test structure, shown in Figs. 1 and 2, is designed to be a scale model of the prototype

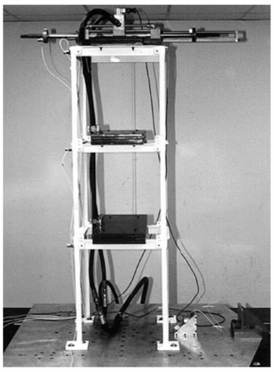

Figure 1. Three Degree-of-Freedom Test Structure with AMD System.

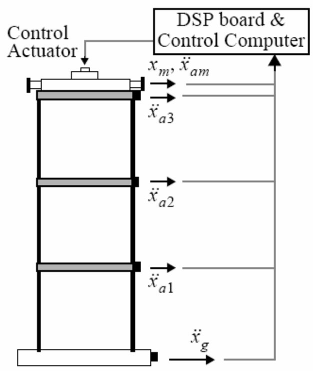

Figure 2. Schematic Diagram of Experimental Setup.

Building discussed in Chung, et al. (1989) and is subject to one-dimensional ground motion. The building frame is constructed of steel, with a height of 158 cm. The floor masses of the model weigh a total of 227 kg, distributed evenly between the three floors. The time scale factor is 0.2, making the natural frequencies of the model approximately five times those of the prototype. The first three modes of the model structural system are at 5.81 Hz, 17.68 Hz and 28.53 Hz, with associated damping ratios given, respectively, by 0.33%, 0.23%, and

0.30%. The ratio of model quantities to those corresponding to the prototype structure are: force = 1:60, mass = 1:206, time = 1:5, displacement = 4:29 and acceleration = 7:2. For control purposes, a simple implementation of an active mass driver (AMD) was placed on the third floor of the structure.

EVALUATION MODEL:

The model used for controller design and analysis is the evaluation model described in previous section. This model has 28 states and it is given by the following equations:

$$\dot{x} = Ax + E\ddot{x}_g + Bu \quad (1a)$$
$$y = C_y x + F_y \ddot{x}_g + D_y u, \quad (1b)$$

Where x is the state vector, $\ddot{x}_g$ is the ground acceleration, u is a scalar control input, and y is the measurement vector available to the controller. The measurement vector y is partitioned into $y^T = [y_1^T \; y_2]$ where:

$$y_1 = \begin{bmatrix} x_m \\ \ddot{x}_{a1} \\ \ddot{x}_{a2} \\ \ddot{x}_{a3} \\ \ddot{x}_{am} \end{bmatrix} \text{ and } y_2 = \ddot{x}_g. \quad (2)$$

$$y^T = [y_1^T \; y_2] \quad (3)$$

$$U=K.X \quad (4)$$

The units of the control input u and the measurement y are volts; thus, the input-output map from u to y is nondimensional. No attempt is made to reduce the order of the model for design purposes. This is because the number of states is within the range that can be handled by the design methods used in this paper. The controllers are designed using continuous-time methods without taking into account time/amplitude quantizations; these discriminations are incorporated later to obtain the implementable control laws.

EVALUATION CRITERIA AND IMPLEMENTATION CONSTRAINTS:

The evaluation criteria and implementation constraints are denoted in Spencer et al (1997) and repeated here for completeness.

Stochastic evaluation criteria

In this case, the ground acceleration $\ddot{x}_g$ is a stationary stochastic process with power spectral density:

$$S_{\ddot{x}_g\ddot{x}_g}(\omega, \omega_g, \zeta_g) = S_0(\omega_g, \zeta_g)\frac{4\zeta_g^2\omega_g^2\omega^2 + \omega^4}{\left(\omega^2 - \omega_g^2\right)^2 + 4\zeta_g^2\omega_g^2\omega^2} \quad (5)$$

Where the natural frequency ω_g and the damping ratio ξ_g lie in prescribed intervals. The scaling factor S_0 keeps constant the RMS value of the ground acceleration irrespective of changes in ω_g and ξ_g. In addition to this ground disturbance, the entire measurement vector y is corrupted by the measurement noise v. Each component of the measurement noise is modeled as a stationary white noise process. When both the random ground disturbance and the measurement noise are applied to the structure, the effectiveness of the controller is to be measured by the following criteria:

$$\begin{aligned} J_1 &= \max\left\{\frac{\sigma_{d1}}{\sigma_{x_{30}}}, \frac{\sigma_{d2}}{\sigma_{x_{30}}}, \frac{\sigma_{d3}}{\sigma_{x_{30}}}\right\} & J_4 &= \max\left\{\frac{\sigma_{\dot{x}_m}}{\sigma_{\dot{x}_{30}}}\right\} \\ J_2 &= \max\left\{\frac{\sigma_{\ddot{x}_{a1}}}{\sigma_{\ddot{x}_{a30}}}, \frac{\sigma_{\ddot{x}_{a2}}}{\sigma_{\ddot{x}_{a30}}}, \frac{\sigma_{\ddot{x}_{a3}}}{\sigma_{\ddot{x}_{a30}}}\right\} & J_5 &= \max\left\{\frac{\sigma_{\ddot{x}_{am}}}{\sigma_{\ddot{x}_{a30}}}\right\} \\ J_3 &= \max\left\{\frac{\sigma_{x_m}}{\sigma_{x_{30}}}\right\} \end{aligned} \tag{6}$$

Where the interstory drifts d_i are the relative lateral displacements between floors ($d_1 = x_1$,$d_2 = x_2$-x_1, $d_3 = x_3$-x_2), $\dot{x}_i$ is the lateral velocity of floor i, and $\ddot{x}_{ai}$ represents the absolute lateral acceleration of floor i. The signals x_m, $\dot{x}_m$ and $\ddot{x}_{am}$ are the displacement (relative to the 3rd floor), velocity and absolute acceleration of the active mass driver. Finally, the normalization constants σ_{x30} , $\sigma_{\dot{x}30}$, and $\sigma_{\ddot{x}a30}$ are, respectively, the worst case RMS values of the 3rd floor position, velocity and absolute acceleration, over all allowed values of ω_g and ξ_g, when the loop is open. In addition, the following hard constraints must be met

$$\sigma_u \leq 1 \text{ v}, \quad \sigma_{\ddot{x}_{am}} \leq 2 \text{ g}, \quad \sigma_{x_m} \leq 3 \text{ cm}. \tag{7}$$

The criteria (6) and the RMS values dening the constraints (7) depend on the parameters ω_g and ξ_g of the disturbance model (5). When evaluating the criteria, and constraints, for a given controller, these quantities need to be maximized over ω_g and ξ_g to determine the worst possible values. This is to be done using the following ranges

$$3.18 \text{ Hz} \leq \omega_g \leq 19.1 \text{ Hz}, \quad 0.3 \leq \zeta_g \leq 0.7. \tag{8}$$

Deterministic evaluation criteria

In this case, the ground acceleration is one of two historical earthquake records: 1940 El Centro NS and 1968 Hachinohe NS. The controller is evaluated according to the following criteria:

$$\begin{aligned} J_6 &= \max_{\substack{\text{El Centro} \\ \text{Hachinohe}}} \max_t \left\{\frac{|d_1(t)|}{x_{30}}, \frac{|d_2(t)|}{x_{30}}, \frac{|d_3(t)|}{x_{30}}\right\} & J_9 &= \max_{\substack{\text{El Centro} \\ \text{Hachinohe}}} \max_t \frac{|\dot{x}_m(t)|}{\dot{x}_{30}} \\ J_7 &= \max_{\substack{\text{El Centro} \\ \text{Hachinohe}}} \max_t \left\{\frac{|\ddot{x}_{a1}(t)|}{\ddot{x}_{a30}}, \frac{|\ddot{x}_{a2}(t)|}{\ddot{x}_{a30}}, \frac{|\ddot{x}_{a3}(t)|}{\ddot{x}_{a30}}\right\} & J_{10} &= \max_{\substack{\text{El Centro} \\ \text{Hachinohe}}} \max_t \frac{|\ddot{x}_{am}(t)|}{\ddot{x}_{a30}} \\ J_8 &= \max_{\substack{\text{El Centro} \\ \text{Hachinohe}}} \max_t \frac{|x_m(t)|}{x_{30}} \end{aligned} \tag{9}$$

Where x_{30}, $\dot{x}_{30}$ and $\ddot{x}_{a30}$ are the largest peak values, taken over both earthquake records, of the 3rd floor position, velocity and absolute acceleration, respectively, when no controller is present. In addition, the following hard constraints must be met:

$$\max_{\substack{\text{El Centro}\\ \text{Hachinohe}}} \max_t |u(t)| \leq 3 \text{ v} \qquad \max_{\substack{\text{El Centro}\\ \text{Hachinohe}}} \max_t |x_m(t)| \leq 9 \text{ cm.} \qquad (10)$$

$$\max_{\substack{\text{El Centro}\\ \text{Hachinohe}}} \max_t |\ddot{x}_{am}(t)| \leq 6 \text{ g}$$

Evaluation criteria for the peak responses are non–dimensionalized with respect to the corresponding uncontrolled peak third floor responses. For the El Centro earthquake, x_{3o} = 3.37 cm, $\dot{x}_{3o}$ =131 cm/sec, and $\ddot{x}_{a3o}$ = 5.05 g. For the Hachinohe Earthquake, x_{3o} = 1.66 cm, $\dot{x}_{3o}$= 58.3 cm/sec and $\ddot{x}_{a3o}$ = 2.58 g are used.

The SIMULINK (1994) model has been developed to simulate the features and limitations of this structural control problem. Note that, although the controller is digital, the structure is still modeled as a continuous system. To reduce integration errors, a time step of 0.0001 sec is used in the simulation.

GENETIC ALGORITHMS (GAS)

The GA is a stochastic global search method that mimics the metaphor of natural biological evolution. GA operates on a population of potential solutions applying the principle of survival of the fittest to produce (hopefully) better and better approximations to a solution. At each generation, a new set of approximations is created by the process of selecting individuals according to their level of fitness in the problem domain and breeding them together using operators borrowed from natural genetics. This process leads to the evolution of populations of individuals that are better suited to their environment than the individuals that they were created from, just as in natural adaptation. Individuals, or current approximations, are encoded as strings, chromosomes, composed over some alphabet(s), so that the genotypes (chromosome values) are uniquely mapped onto the decision variable (phenotypic) domain. The most commonly used representation in GAs is the binary alphabet {0, 1} although other representations can be used, ternary, integer, real-valued etc.

REAL-CODED DISTRIBUTED GENETIC ALGORITHMS

Real-Coded Genetic Algorithms:

The use of real-valued genes in GAs is claimed by Wright (1991) to offer a number of advantages in numerical function optimization over binary encodings. Efficiency of the GA is increased as there is no need to convert chromosomes to phenotypes before each function evaluation; less memory is required as efficient floating-point internal computer representations can be used directly; there is no loss in precision by discretisation to binary or other values; and there is greater freedom to use different genetic operators. The use of real-valued encodings is described in detail by Michalewicz (1992) and in the literature on Evolution Strategies.

Distributed Genetic Algorithms:

In DGA premise lies in partitioning the population into several subpopulations, each one of them being processed by a GA, independently of the others. Furthermore, a migration mechanism produces a chromosome exchange between the subpopulations. DGA's attempt to overcome premature convergence by preserving diversity due to the semi-isolation of the subpopulations. Another important advantage is that they may be implemented easily on parallel hardware that is very useful method for tall structures where that we have work with extensive parameters. DGA behavior is strongly determined by the migration mechanism's action. In most implementations of this mechanism, copies of the individuals who are subject to migration are sent to one or more neighboring subpopulations. Kröger et al (1999). Call this immigration. Additionally, they investigated emigration, in which individuals leave their subpopulation, and migrate to exactly one of the neighboring subpopulations. Experimental results indicated that the migration strategy of emigration works best. The most general migration strategy is that of unrestricted migration. Here, individuals may migrate from any subpopulation to another.

THE OBJECTIVE AND FITNESS FUNCTIONS:

The objective function is used to provide a measure of how individuals have performed in the problem domain. In the case of a minimization problem, the fit individuals will have the lowest numerical value of the associated objective function. This raw measure of fitness is usually only used as an intermediate stage in determining the relative performance of individuals in a GA. A fitness function reflects both the objective and a penalty for constraint violation. The fitness function has been constructed in the manner of a sequential unconstrained minimization technique, (i.e., an objective with external penalty functions to handle the constraints). Because the GA does not require derivatives, or even the continuity of the function, several options are available to describe the fitness function. For the present study, the fitness functions to be minimized have been formulated by combining the objective functions ϕ_i and the constraint function g_i for ''n_{cons}'' number of constraints, given by:

$$f_1 = \phi_1 + \sum_{i=1}^{Ncons} C_i \max[0, g_i] \tag{11}$$

where $$\phi_1 = \max_{eartquake\ records}\left[\max_{t,i}\left\{\frac{|d_i(t)|}{d^{\max}}\right\}\right] \tag{12}$$

Where ϕ_i , c_i , and g_i=i_{th} objective function, i_{th} penalty coefficient, and i_{th} constraint violation, respectively. In this study, to simplify the selection of the coefficients, c_i , all of the constraints have been formulated in a scaled form and the same value of c_i has been used for all the constraints. In the scaled form, constraint functions have been posed as given in Eq.13 to enforce a value greater than the allowed value, or as in Eq.14 to enforce a value less than the allowed value. These functions are negative valued when the constraints are satisfied and positive valued when violated:

$$g_i = 1 - \frac{\text{actual value}}{\text{allowed}} \leq 0 \tag{13}$$

$$g_i = \frac{\text{actual value}}{\text{allowed}} - 1 \leq 0 \tag{14}$$

SELECTION:

Selection is the process of determining the number of times, or trials, a particular individual are chosen for reproduction and, thus, the number of offspring that an individual will produce. The selection of individuals can be viewed as two separate processes:

1) Determination of the number of trials an individual can expect to receive, and

2) Conversion of the expected number of trials into a discrete number of offspring.

Stochastic universal sampling (SUS) used in this paper is a single-phase sampling algorithm with minimum spread and zero bias. Instead of the single selection pointer employed in roulette wheel methods, SUS uses N equally spaced pointers, where N is the number of selections required. The population is shuffled randomly and a single random number in the range [0 *Sum*/*N*] is generated, *ptr*. The N individuals are then chosen by generating the N pointers spaced by 1, [*ptr*, *ptr*+1, ..., *ptr*+*N*-1], and selecting the individuals whose fatnesses span the positions of the pointers.

INTERMEDIATE RECOMBINATION:

Given a real-valued encoding of the chromosome structure, intermediate recombination is a method of producing new phenotypes around and between the values of the parent's phenotypes. Offspring are produced according to the rule,

$$O_1=P_1+\alpha(P_2-P_1) \qquad (15)$$

Where α is a scaling factor chosen uniformly at random over some interval, typically [-0.25, 1.25] and P1 and P2 are the parent chromosomes. Each variable in the offspring is the result of combining the variables in the parents according to the above expression with a new α chosen for each pair of parent genes. In geometric terms, intermediate recombination is capable of producing new variables within a slightly larger hypercube than that defined by the parents but constrained by the range of α.

MUTATION:

With non-binary representations, mutation is achieved by either perturbing the gene values or random selection of new values within the allowed range. Wright (1991) and Janikow et al. (1991) demonstrate how real-coded GAs may take advantage of higher mutation rates than binary-coded GAs, increasing the level of possible exploration of the search space without adversely affecting the convergence characteristics. Many variations on the mutation operator have been proposed. For example, biasing the mutation towards individuals with lower fitness values to increase the exploration in the search without losing information from the fitter individuals or parameterising the mutation such that the mutation rate decreases with the population convergence. Mühlenbein (1993) has introduced a mutation operator for the real-coded GA that uses a non-linear term for the distribution of the range of mutation applied to gene values.

DGA-BASED CONTROLLER

The control signal is calculated from Eq.16. Where K_r is the state feedback gain matrix with 10 elements and X_r is the 10-dimensional state of reduced order system. In the proposed method K_r is determined by using DGA to minimize the Eq.6 and Eq.9 with constraints shown in Eq.10.

$$U_r = K_r \,.\, X_r \quad \text{where} \quad K_r = [k_1, k_2, \ldots, k_9, k_{10}] \qquad (16)$$

NUMERICAL RESULTS

Real-Coded Distributed Genetic Algorithm (DGA) based control method has examined on benchmark problem. The developed controller on El-Centro and Hachinohe earthquake

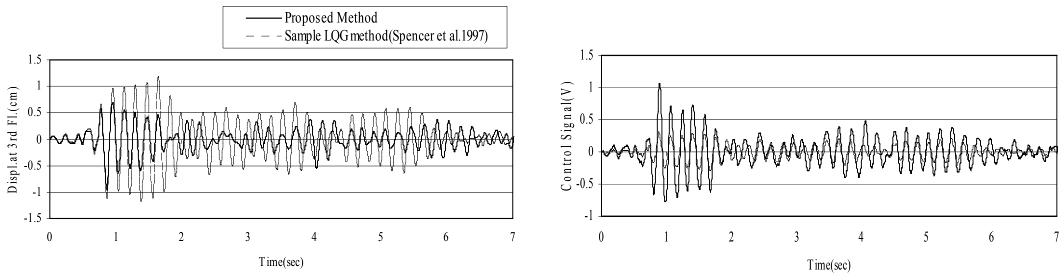

Fig.5: Proposed Control Method and Sample LQG Method Responses under Hachinohe Earthquake

Ground motion data provided by the benchmark problem has been used. The results of Real-Coded DGA based controller have been compared with several other control methods (the benchmark test results of Fuzzy control , LQG method, H_∞ Control , Covariant Control and Sliding mode control methods) are compared with Real-Coded DGA method in Table-I.

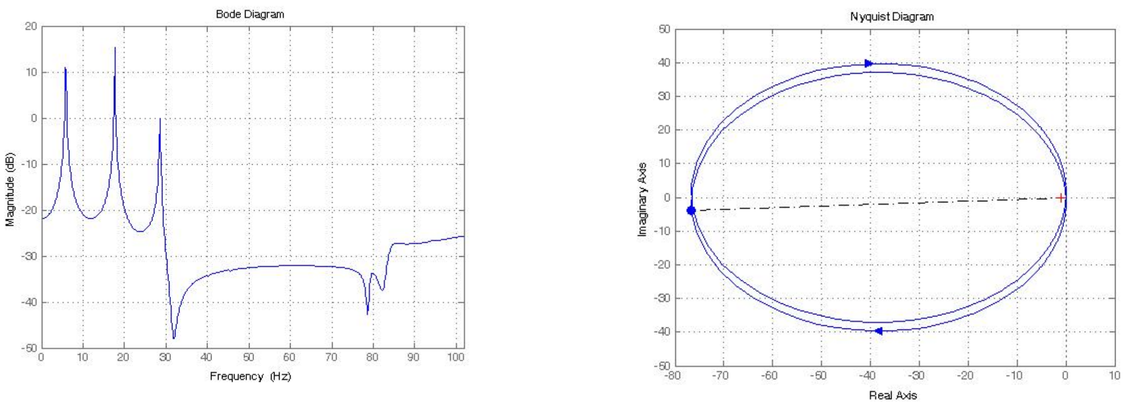

Fig.6. Loop Gain Transfer Function and Nyquist Diagram of Transfer Function from Ground Acceleration to 2nd Floor Acceleration

Results show that the proposed method reduces the responses of the structure as well as required peak control force very effectively in comparing with other controllers. The results showing the efficiency of proposed method much better than sample LQG and other controllers (Fig.5). The loop gain transfer function is used to examine the closed loop stability of the system. The sample LQG controller was considered to be robust in the design if the magnitude of the loop gain was below -5dB at all frequency above 35 Hz. The loop gain transfer function of Real-Coded DGA controller satisfy the same stability and robustness criteria used in the sample LQG controller design (Fig.6). The controlled responses using DGA controller are compared

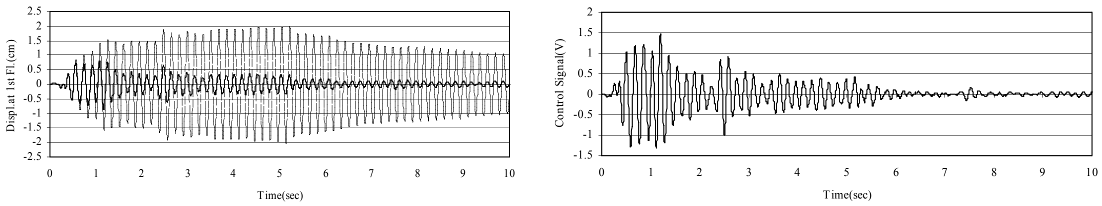

Fig.7: Proposed Control Method and Uncontrolled Responses under El-Centro Earthquake

With uncontrolled responses under two historic earthquakes the El-Centro and Hachinohe in Fig.7 respectively.

	Proposed Method	GA-based control (Case B)	Sample LQG Control*	Covariance control* (3^{rd} iteration)	Fuzzy control* (Case B)	H∞ control* (set S2)	Sliding mode control*
J_1	0.1520	0.1939	0.283	0.2762	0.3232	0.2213	0.1979
J_2	0.2289	0.2886	0.440	0.4205	0.5087	0.3393	0.2936
J_3	0.5347	0.8071	0.510	0.5161	0.4894	0.7054	0.8221
J_4	0.7280	0.7685	0.513	0.5200	0.4137	0.6994	0.8042
J_5	0.6239	0.6974	0.628	0.5001	0.5981	0.7219	0.7775
J_6	0.3471	0.3673	0.456	0.4369	0.4748	0.3859	0.3738
J_7	0.6481	0.6731	0.711	0.6908	0.8666	0.7097	0.6674
J_8	2.2699	1.8144	0.670	0.7197	0.6249	1.0826	1.6832
J_9	2.0438	1.5162	0.775	0.9257	0.6474	1.1078	1.4903
J_{10}	1.813	1.0632	1.340	1.0589	1.2994	0.9614	1.5673

Table-I: Evaluation Criteria Compared with other Control Methods

CONCLUSIONS

The DGA Based method applied to a benchmark problem- an Active Mass Driver (AMD) system. A design example of practical Benchmark problem is given showing the flexibility and simplicity of this type of control system also specification and performance achieved. It has been shown that this method's performance in the response reduction is far superior to that of the other control methods. The robustness of the DGA base controller satisfies the same stability and robustness criteria used in the sample LQG controller design. The results are compared with other control methods.

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