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ACTIVE VIBRATION CONTROL WITH GENETIC ALGORITHMS

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Abstract

This paper presents an investigation into the development of an adaptive active control mechanism for vibration suppression using genetic algorithms (GAs). GAs are used to estimate the adaptive controller characteristics, where the controller is designed on the basis of optimal vibration suppression using the plant model. This is realised by minimising the prediction error of the actual plant output and the model output. A MATLAB GA toolbox is used to identify the controller parameters. A comparative performance of the conventional recursive least square (RLS) scheme and the GA is presented. The active vibration control system is implemented with both the GA and the RLS schemes, and its performance assessed in the suppression of vibration along a flexible beam structure in each case.

Key words: Active vibration control, genetic algorithms, recursive least squares, flexible beam structure.

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1 Introduction

Active vibration control (AVC) consists of artificially generating cancelling source(s) to destructively interfere with the unwanted source and thus result in a reduction in the level of the vibration (disturbances) at desired location(s) in a structure. This is realised by detecting and processing the vibration by a suitable electronic controller so that, when superimposed on the disturbances, cancellation occurs. Due to the broadband nature of the disturbances, it is required that the control mechanism in an AVC system realises suitable frequency-dependent characteristics so that cancellation over a broad range of frequencies is achieved. In practice, the spectral contents of the disturbances as well as the characteristics of system components are, in general, subject to variation, giving rise to time-varying phenomena. This implies that the control mechanism is further required to be intelligent enough to track these variations so that the desired level of performance is achieved and maintained (Tokhi and Leitch, 1991a).

A flexible beam system, fixed at one end and free at another end, in transverse vibration is considered in this paper. Such a system has an infinite number of modes, although in most cases the lower modes are the dominant ones requiring attention. The unwanted vibrations in the structure are assumed to be due to a single point disturbance of broadband nature. First order central finite difference (FD) methods are used to study the behaviour of the beam and develop a suitable test and verification platform. An AVC system is designed utilising a feedforward control structure to yield optimum cancellation of broadband vibration at an observation point along the beam. The controller design relations are formulated such that to allow on-line design and implementation and, thus, yield a self-tuning control algorithm.

Many attempts have been made in the past at devising methods of tackling the problems arising due to unwanted structural vibrations (disturbances). Traditional methods of vibration suppression include passive methods which consist of mounting passive material on the structure. These methods are efficient at high frequencies but expensive and bulky at low frequencies. Moreover, the current trend towards light-weight, hence flexible, structures has imposed a further limitation to the utilisation of passive methods, specially for low-frequency vibration suppression. Active vibration control is found to be more efficient and economical than passive methods at low-frequency vibration suppression. Thus, to achieve vibration suppression over the full (low-high) frequency range, a hybrid control method incorporating active techniques for low-frequency and passive techniques for high-frequency vibration suppression can be utilised (Leitch and Tokhi, 1987).

Active vibration control is not a new concept. It is based on the principles that were initially proposed by Lueg in the early 1930s for noise cancellation (Lueg, 1936). Since then a considerable amount of research work has been devoted to the development of methodologies for the design and realisation of AVC systems in various applications (Baz and Poh, 1988; Baz and Ro, 1991; Doelman, 1991; Elliott, et. al., 1987; Kourmoulis, 1990; Synder and Hansen, 1991; Tokhi and Leitch, 1991a,b,c). An AVC system is realised by detecting the primary (unwanted) disturbances through detection sensor(s) and processing these by an electronic controller of suitable transfer characteristics to drive the secondary source(s) (actuators) so that when the secondary wave is superimposed on the primary wave the two destructively interfere with one another and cancellation occurs. Active vibration control mechanisms developed generally concentrate on reducing the level of vibrations at selected resonance modes of the system. In doing so, problems related to observation and/or control spill-over due to un-modelled dynamics of the system arise. These problems can be avoided by designing an AVC system that incorporates a suitable system identification algorithm through which an appropriate model of the system can be developed within the frequency range of interest. The AVC system presented in this paper includes an on-line system identification algorithm which gives a suitable model of the system in parametric form within a broad range of frequencies of interest. The model thus obtained is then used to design the required controller and generate the corresponding control signal so that to reduce the level of vibration over this broad frequency range.

D.E

The evolutionary genetic algorithm, imitating the collective learning paradigm of natural populations, is based upon Darwin's observations and the modern synthetic theory of evolution. A genetic algorithm is a parallel global search technique that emulates natural genetic operators. Since it simultaneously evaluates many points in the parameter space, it is more likely to converge toward the global solution. It needs not to assume that the search space is differentiable or continuous, and can also iterate several times on each datum received. A GA applies operators inspired by the mechanics of natural selection to a population of binary strings encoding the parameter space. At each generation, it explores different areas of the parameter space, and then directs the search to regions where there is a high probability of finding improved performance. By working with a population of solutions the algorithm can in effect search many local minima and thereby increases the likelihood of finding the global minima. The GAs were first introduced in the 1960s, embedding into the general framework of adaptation (Holland, 1975). During the last two decades, a substantial amount of research work has been carried out both in engineering and non-engineering disciplines (Chipperfield, et. al., 1994; Flockton and White, 1993; Goldberg, 1989). Although GAs have gained popularity as parallel, global search techniques, their use in area of active control is very limited (Kristinsson and Dumont, 1992).

This paper presents an investigation into the use of GAs to estimate the adaptive controller characteristics, where the controller is designed based on the plant model. This is realised by minimising the prediction error of the actual plant output and the model output. A MATLAB GA toolbox is utilised to identify the controller parameters. A comparative performance of the conventional RLS scheme and the GA is presented. The AVC algorithm is implemented with both the GA and the RLS schemes and its performance assessed in the suppression of vibration along a flexible beam structure.

2 The flexible beam system

A schematic diagram of the cantilever beam system is shown in Figure 1, where L represents the length of the beam, $U(x,t)$ represents an applied force at a distance x from the fixed (clamped) end of the beam at time t and $y(x,t)$ is the deflection of the beam from its stationary (unmoved) position at the point where the force has been applied. The motion of the beam in transverse vibration is governed by the well known fourth-order partial differential equation (PDE) (Kourmoulis, 1990)

$$\mu^2 \frac{\partial^4 y(x,t)}{\partial x^4} + \frac{\partial^2 y(x,t)}{\partial t^2} = \frac{1}{m} U(x,t) \tag{1}$$

where μ is a beam constant given by $\mu^2 = \frac{EI}{\rho A}$, with ρ, A, I and E representing the mass density, cross-sectional area, moment of inertia of the beam and the Young modulus respectively, and m is the mass of the beam. The corresponding boundary conditions at the fixed and free ends of the beam are given by

$$\begin{gathered} y(0,t) = 0 \quad \text{and} \quad \frac{\partial y(0,t)}{\partial x} = 0 \\ \frac{\partial^2 y(L,t)}{\partial x^2} = 0 \quad \text{and} \quad \frac{\partial^3 y(L,t)}{\partial x^3} = 0 \end{gathered} \tag{2}$$

Note that the model thus utilised incorporates no damping. To construct a suitable platform for test and verification of the control mechanism (introduced later), a method of obtaining numerical solution of the PDE in equation (1) is required. This can be achieved by using the finite difference (FD) method. The finite element (FE) method has commonly been used in the past for obtaining numerical solutions of the PDE and for constructing simulation environments characterising the behaviour of such systems. This method allows irregularities in the structure and mixed boundary conditions to be handled. However, these are not of concern in the case of a uniform beam structure considered here. For the system considered here, the dynamics may efficiently be described in terms of a modal expansion. However, a virtue of the FD method is that it could fairly readily be applied to more complicated mechanical systems, for which an analytic modal solution could not be readily obtained. Therefore, the FD method is used here for obtaining a numerical solution of the PDE in equation (1) and for constructing a suitable simulation environment characterising the behaviour of the beam.

To obtain a solution to the PDE, describing the beam motion, the partial derivative terms $\frac{\partial^4 y(x,t)}{\partial x^4}$ and $\frac{\partial^2 y(x,t)}{\partial t^2}$ in equation (1) and the boundary conditions in equation (2) are approximated using first order central FD approximations. This involves a discretisation of the beam into a finite number of equal-length sections (segments), each of length Δx, and considering the beam motion (deflection) for the end of each section at equally-spaced time steps of duration Δt. In this manner, let $y(x,t)$ be denoted by $y_{i,j}$ representing the beam deflection at point i at time step j. Let $y(x+v\Delta x, t+w\Delta t)$ be denoted by $y_{i+v,j+w}$, where v and w are non-negative integer numbers. Using first-order central FD methods to approximate the partial derivative terms in equations (1) and (2) yields (Tokhi and Hossain, 1994a)

$$Y_{j+1} = -Y_{j-1} - \lambda^2 S Y_j + (\Delta t)^2 U(x,t)\frac{1}{m} \tag{3}$$

where,

$$Y_{j+1} = \begin{bmatrix} y_{1,j+1} \\ y_{2,j+1} \\ \vdots \\ y_{n,j+1} \end{bmatrix},\quad Y_j = \begin{bmatrix} y_{1,j} \\ y_{2,j} \\ \vdots \\ y_{n,j} \end{bmatrix},\quad Y_{j-1} = \begin{bmatrix} y_{1,j-1} \\ y_{2,j-1} \\ \vdots \\ y_{n,j-1} \end{bmatrix},$$

and S is a matrix given (for $n = 19$, say) as

$$S = \begin{bmatrix} a & -4 & 1 & 0 & 0 & 0 & \cdots & \cdots & 0 \\ -4 & b & -4 & 1 & 0 & 0 & \cdots & \cdots & 0 \\ 1 & -4 & b & -4 & 1 & 0 & \cdots & \cdots & 0 \\ 0 & 1 & -4 & b & -4 & 1 & \cdots & \cdots & 0 \\ \cdots & \cdots & \cdots & \cdots & \cdots & \cdots & \cdots & \cdots & \cdots \\ \cdots & \cdots & \cdots & \cdots & \cdots & \cdots & \cdots & \cdots & \cdots \\ \cdots & \cdots & \cdots & \cdots & 1 & -4 & b & -4 & 1 \\ \cdots & \cdots & \cdots & \cdots & 0 & 1 & -4 & c & -2 \\ \cdots & \cdots & \cdots & \cdots & 0 & 0 & 2 & -4 & d \end{bmatrix}$$

where, $a = 7 - \frac{2}{\lambda^2}$, $b = 6 - \frac{2}{\lambda^2}$, $c = 5 - \frac{2}{\lambda^2}$, $d = 2 - \frac{2}{\lambda^2}$ and $\lambda^2 = \frac{(\Delta t)^2}{(\Delta x)^4}\mu^2$. Equation (3) is the required relation for the simulation algorithm, characterising the behaviour of the cantilever beam system, which can be implemented on a digital computer easily. For the algorithm to be stable it is required that the iterative scheme described in equation (3), for each grid point, converges to a solution. It has been shown that a necessary and sufficient condition for stability satisfying this convergence requirement is given by $0 < \lambda^2 \leq 0.25$ (Kourmoulis, 1990).

To investigate the real-time implementation of the simulation algorithm and study the behaviour of the system an aluminium type cantilever beam of length $L=0.635$ m; mass $m=0.037\ kg$ and $\mu=1.351$ was considered. The first five resonance modes of this beam, as obtained through theoretical analysis, are located at *1.875* Hz, *11.751* Hz, *32.902* Hz, *64.476* Hz and *106.583* Hz respectively with the first two modes dominantly representing the behaviour of the beam. It was found through numerical simulations that for the purpose of this investigation reasonable accuracy in representing the first few (dominant) modes of vibration is achieved by dividing the beam into 19 segments ($n=19$). Therefore, $n=19$ was chosen throughout the investigations presented in this paper. Moreover, for the algorithm to be stable a sample period $\Delta t = 0.3$ *msec* which is sufficient to cover all the resonance modes of vibration of the beam was selected giving a value of $\lambda=0.3629$.

The behaviour of the beam in transverse vibration was studied by implementing the simulation algorithm in real-time on a SUN workstation. Although in simulation experiments the speed of implementation of the process involved is not of major concern and thus a general purpose digital computing facility could be utilised instead. In practical investigations, however, it is essential for the computing system to meet the real-time processing requirements of the algorithm(s) involved.

Figure 2 shows the end-point response and the corresponding spectral density of the beam to a PRBS disturbance force of $\pm 0.1N$, applied at grid point 12. The first five resonance modes, as obtained from these results, are located at 2 Hz, *11* Hz, *30* Hz, *57* Hz and *91* Hz respectively. These, as compared with the corresponding theoretical values, are within reasonably acceptable limits, for purposes of this investigation. It is seen in Figure 2 that the level of the first resonance mode is much more dominant than the rest. Therefore, substantial reduction in the overall level of vibration will be achieved if the first mode is cancelled by a vibration control system. Note further in Figure 2 that the first mode of vibration appears to be dominantly characterising the beam fluctuation. In general, two factors, namely, the nature of the disturbance including its amplitude and frequency contents and the location at which it is applied determine the dynamic modes of the structure that are excited and the level at which these modes will appear.

3 The active vibration control system

A schematic diagram of an AVC structure is shown in Figure 3(a). An unwanted (primary disturbance) point source emits broadband disturbance into the structure. This is detected by a detector, processed by a controller of suitable transfer characteristics and fed to a cancelling (secondary) point actuator. The secondary (control) signal thus generated interferes with the disturbance so that to achieve a reduction in the level of vibration at an observation point along the structure.

A frequency-domain equivalent block diagram of the AVC structure is shown in Figure 3(b), where *E, F, G* and *H* are transfer functions of the paths between the primary source and the detector, secondary source and the detector, primary source and the observer and secondary source and the observer respectively. M, M_o, C and L are transfer characteristics of the detector, the observer, the controller and the secondary source respectively. U_D and U_C are the primary and secondary signals at the source locations, whereas, Y_{OD} and Y_{OC} are the corresponding signals at the observation point respectively. U_M is the detected signal and Y_O is the observed signal. The block diagram in Figure 3(b) can be thought of either in the continuous frequency (s) domain or discrete frequency (z) domain. Therefore, unless specified, the analysis and design developed in this paper apply to both the continuous-time and the discrete-time domains.

For complete cancellation of the noise to be achieved at the observation point Y_O must be forced to become zero. This is equivalent to the minimum variance design criterion in a stochastic environment. This requires the primary and secondary signals at the observation point to be equal in amplitudes and have a phase difference of 180^0 relative to one another. Thus, synthesising the controller within the block diagram of Figure 3(b) on the basis of this objective yields

$$C = \frac{G}{ML(FG - EH)} \tag{4}$$

Equation (4) is the required controller transfer function for optimum cancellation of broadband vibration at the observation point.

Note in equation (4) that, for given secondary source and detector the controller characteristics are determined by the geometric arrangement of system components. This incorporates the location of the detector and the observer with respect to the primary and secondary sources. Among these, there exist arrangements that will lead to the denominator, $FG - EH$, in equation (4) approaching zero and thus requiring the controller to have impractically large gain. Thus, an analysis of the system on this basis yielding the locus of detection and observation points for which the controller will be required to have an impractically large gain for optimum cancellation is required at a design stage (Tokhi and Leitch, 1991c). Moreover, note in Figure 3 that the secondary signals reaching the detector form a positive feedback loop that can cause the system to become unstable for certain geometrical arrangements of system components. Therefore, an analysis of the system from a stability point of view leading to a robust design of the system is important at a design stage.

3.1 Self-tuning active vibration control

In practice, the characteristics of sources of vibration vary due to operating conditions leading to time-varying spectra. Moreover, the characteristics of transducers, sensors and other electronic equipment used are subject to variation due to environmental effects, ageing, etc. Therefore, an AVC system is required to be design so that the controller characteristics are updated in accordance with the changes in the system such that the required performance is achieved and maintained. To achieve this a self-tuning control strategy, allowing on-line design and implementation of the controller, can be utilised.

Self-tuning control is distinguished as a class of adaptive control mechanisms (Astrom and Wittenmark, 1995; Tokhi and Leitch, 1992; Wellstead and Zarrop, 1991). It essentially consists of the processes of identification and control, both implemented on-line. The identification process is mainly concerned with on-line modelling of the plant to be controlled and, thus, incorporates a suitable system identification algorithm. The control process, on the other hand, is concerned with the design and implementation of the controller using the plant model and, thus, incorporates a suitable controller design criterion. In this manner, various types of self-tuning control algorithm can be designed depending on the type of the identification algorithm and controller design strategy employed. Many system identification schemes have been used in self-tuning control algorithms. Among these, the recursive form of the least squares algorithm is the most common self-tuning identifier. In a similar manner, several controller design criteria have been used in self-tuning control algorithms. Among these, the most common ones are the minimum variance and pole assignment designs. A self-tuning control algorithm can either be designed as an explicit combination of identification of a plant model and controller design or as an implicit algorithm in which the controller is identified directly (bypassing identification of the plant model). Each of these algorithms have their advantages and disadvantages which depend mainly on the type of application and availability of resources for implementation. Self-tuning is, in a sense, the simplest possible adaptive control algorithm derivable from the point of view of the discrete-time stochastic control theory. An attractive property of the self-tuning controller is that under most reasonable circumstances, as the number of input and output samples tends to infinity, it will converge to the optimal controller that would be obtained if the system parameters are exactly known. Moreover, the strategy is simple enough to allow the use of digital processors for implementing self-tuning controllers, thus promising a relatively low cost solution to complex control problems. In this paper an explicit self-tuning AVC algorithm, incorporating RLS and GAs based parameter estimation algorithms and the minimum variance design criterion, is developed.

To allow the development of a self-tuning AVC algorithm, consider the system in Figure 4 with the detected signal, U_M, as input and the observed signal, Y_O, as output. Moreover, owing to the state of the secondary source let the system behaviour be characterised by two sub-systems, namely, when the secondary source is *off*, with an equivalent transfer function denoted by Q_0, and when the secondary source is *on*, with an equivalent transfer function denoted by Q_1. Using the block diagram of Figure 3(b), these can be obtained as

$$Q_0 = \frac{M_o G}{ME} \quad , \quad Q_1 = \frac{M_o G}{ME}\left[1 - \frac{ML(FG - EH)}{G}\right] \tag{5}$$

Note that in obtaining Q_0 and Q_1 in equation (5) the controller block in Figure 3 is replaced simply by a switch; the controller transfer function is not known before an estimation/measurement process. Manipulating equation (5) and using equation (4) yields an equivalent design relation for the controller in terms of Q_0 and Q_1 as

$$C = \left[1 - \frac{Q_1}{Q_0}\right]^{-1} \tag{6}$$

Equation (6) is the required controller design rule given in terms of transfer characteristics Q_0 and Q_1 which can be measured/estimated on-line. An on-line design and implementation of the controller can thus be achieved by obtaining Q_0 and Q_1 using a suitable system identification algorithm, then using equation (6) to calculate the controller transfer function and implementing this on a digital processor. Moreover, to monitor system performance and update the controller characteristics upon changes in the system a supervisory level control can be utilised. This results in a self-tuning AVC mechanism as shown in Figure 4. The 'plant' in Figure 4 designates the system in Figure 3 between the detection and observation points, in which during the identification process the controller is replaced by a switch. During the control process, however, the estimated controller transfer function is implemented to replace the switch. The supervisor is designed to monitor system performance on the basis of a pre-specified quantitative measure of cancellation as an index of performance, so that if the cancellation achieved is within the specified range then the algorithm implementation remains at the control level. However, if the cancellation is outside the specified range then self-tuning is re-initiated at the identification level. The supervisory level can also be facilitated with further levels of intelligence such as monitoring system stability, system performance in a transient period and validation of the plant model at the identification level.

In implementing the self-tuning control algorithm described above, several issues of practical importance need to be given careful consideration. These include properties of the disturbance signal, robustness of the estimation and control, system stability and processor-related issues such as word length, speed and computational power (Tokhi and Hossain, 1994a; Tokhi and Leitch, 1991a).

3.2 Identification

The conventional on-line system identification schemes, such as least squares, instrumental variable, maximum likelihood etc., are in essence local search techniques. These techniques often fail in the search for the global optimum if the search space is not differentiable or linear in the parameters. On the other hand, these techniques do not iterate more than once on each datum received. In contrast, a GA simultaneously evaluates many points in the parameter space and converges towards the global solution. It does not require the search space to be differentiable or continuous and can also iterate several times on each datum received (Kargupta and Smith, 1991; Kristinsson and Dumont, 1992). A genetic algorithm differs from other search techniques by the use of concepts taken from natural genetics and evolution theory. Firstly, the algorithm works with a population of strings, searching many peaks in parallel. By employing genetic operators it exchanges information between the peaks, hence reducing the possibility of ending at a local minimum and missing the global minimum. Secondly, it works with a coding of the parameters, not the parameters themselves. The coding that has been shown to be the optimal one is binary coding. Intuitively, it is better to have few possible options for many bits than to have many options for few bits. Thirdly, the algorithm only needs to evaluate the objective function to guide its search. There is no requirement for derivatives or other auxiliary knowledge. The only available feedback from the system is the value of the performance measure of the current population. Finally, the transition rules are probabilistic rather than deterministic.

A genetic algorithm in its simplest form uses three operators: reproduction/selection, crossover and mutation (Goldberg, 1989; Kargupta and Smith, 1991). These operators are applied iteratively to each generation of individuals. The first operation, reproduction/selection, will choose individuals for mating based on their objective value. The objective value represents how good that solution is and usually requires some form of function to be evaluated. The second operation, crossover, will take these pairs and exchange elements of the data structures. The crossover may result in the offspring progeny having a higher or lower objective value as compared to the parents. The final operation, mutation, will periodically modify parts of the data structure of an individual and, therefore, making it represent a different point in the search-space. Mutation drives the GA into exploring alternative areas of the search-space.

The process of identification is described here as the process of estimating parameters of the required controller characteristics. In this manner, it consists of the processes of estimating the system models Q_0 and Q_1 and the controller design calculation. The RLS algorithm and GAs are used here to estimate the system models Q_0 and Q_1 in the discrete-time domain in parametric form.

The RLS algorithm is based on the well known least squares method. For an unknown plant model, with output $y(n)$, described by

$$y(n) = \Psi(n)\Theta(n)$$

where, Θ is the parameter vector and Ψ, known as the observation matrix, is a row vector of the measured input/output signals, the RLS estimation process at a time step k is described by

$$\varepsilon(k) = \Psi(k)\Theta(k-1) - y(k)$$

$$\Theta(k) = \Theta(k-1) - P(k-1)\Psi^T(k)\left[1 + \Psi(k)P(k-1)\Psi^T(k)\right]^{-1}\varepsilon(k) \tag{7}$$

$$P(k) = P(k-1) - P(k-1)\Psi^T(k)\left[1 + \Psi(k)P(k-1)\Psi^T(k)\right]^{-1}\Psi(k)P(k-1)$$

where, $P(k)$ is the covariance matrix. Thus, the RLS estimation process is to implement and execute the relations in equation (7) in the order given. The performance of the estimator can be monitored by observing the parameter set at each iteration. Once convergence has been achieved the routine can be stopped. The convergence is determined by the magnitude of the modelling error $\varepsilon(k)$ approaching zero or by the estimated set of parameters reaching a steady level (Tokhi and Leitch, 1992).

The GAs are based on the method of minimisation of the prediction error. To estimate the parameters of Q_0 and Q_1 using GAs, the fitness function

$$f(e) = \sum_{n=0}^{q} \left| y(n) - \hat{y}(n) \right| \tag{8}$$

is adopted, where, q is the number of input/output samples, $y(n)$ is the desired (plant) output and the $\hat{y}(n)$ is the estimated model output.

The process of calculation of parameters of the controller uses the design rule in equation (6) with the estimated Q_0 and Q_1. The controller thus obtained can be implemented on-line in discrete form using the equivalent difference equation formulation.

4 Implementation and results

The fitness function in equation (8) was implemented for both Q_0 and Q_1 considering each as a linear discrete second order model. Investigations showed that the convergence vary with changes in the number of individuals or in the representation. Figure 5 shows the convergence of the function over 300 generations. It is noted that the case where parameters of the model are represented by 20 bit strings for 30 individuals offers the best convergence. Thus, this configuration was utilised subsequently throughout this investigation at estimating Q_0 and Q_1. The convergence of prediction errors for Q_0 and Q_1, thus, obtained are shown in Figure 6. Figure 7 shows the desired (plant) output and the estimated model output for the two models using the GA. The corresponding outputs with second order estimated models using the RLS algorithm, are shown in Figure 8. It is noted that, as compared to the RLS estimation, the GA achieved significantly better performance.

To investigate the performance of the self-tuning AVC algorithm a PRBS disturbance force of $\pm 0.1N$ applied at grid-point 12 was used as the unwanted primary disturbance and the control source at grid-point 20. The controller was implemented based on the plant model estimated utilising GAs. Figure 9 shows the response of the beam before and after cancellation at the observation point (grid-point 20). Figure 10 shows the corresponding time-domain representation of beam fluctuation along its length. It was noted, through a spectral density representation of the results in Figure 9, that about 10 dB cancellation was achieved at the first resonance mode. The cancellation at the second resonance mode was 1dB. The vibrations at the third, fourth and fifth resonance modes were slightly reinforced. This was due to low order linear model considered in the estimation process mainly to account for the highly dominant modes. This suggests that better cancellation may be achieved with a higher order model or by using a non-linear model.

To compare with conventional RLS based AVC system, the controller was also implemented in a similar manner utilising the RLS estimator. Figure 11 shows the performance of the RLS based AVC system at the observation point. The corresponding time-domain fluctuation along the beam length is shown in Figure 12. It was noted, through a spectral density representation of the results in Figure 11, that about 8 dB cancellation was achieved at the first resonance mode and 0.28 dB at the second resonance mode. The vibrations at the third and fourth resonance modes were slightly reinforced. Thus, it can be concluded from this investigation that the conventional RLS based AVC system is unimpressive as compared to the GA based system.

It was noted in the experiments above that the execution time of the GA based algorithm is more than that of the conventional scheme with the same computing platform. However, high performance computing techniques for instance parallel computing, could provide suitable solutions for the real-time implementation of the GA based algorithm (Tokhi and Hossain, 1994b, 1995). It is important to note that the GA is based on probabilistic rules, and there is no guarantee that the controller will always stabilise the plant. This problem could, however, be addressed by incorporating a monitoring mechanism within the system.

5 Conclusion

The design and implementation of a GA and RLS based adaptive AVC algorithm for flexible beam structures has been presented, discussed, and verified through numerical simulation. A supervisory level control has been incorporated within the algorithm which allows on-line monitoring of system performance and controller adaptation. The performance of both algorithms have been verified in the suppression of broadband vibration in a flexible beam system. This investigation has demonstrated that better estimation of a system model is achieved using GAs as compared to a conventional RLS scheme. Consequently, the system incorporating the GA based estimator has achieved better performance as compared to that using RLS based estimator. However, it has been demonstrated that cancellation at the higher modes has not been impressive in both cases. This has also established future direction for investigation towards using higher order linear models and utilisation of non-linear models using GAs for AVC systems.

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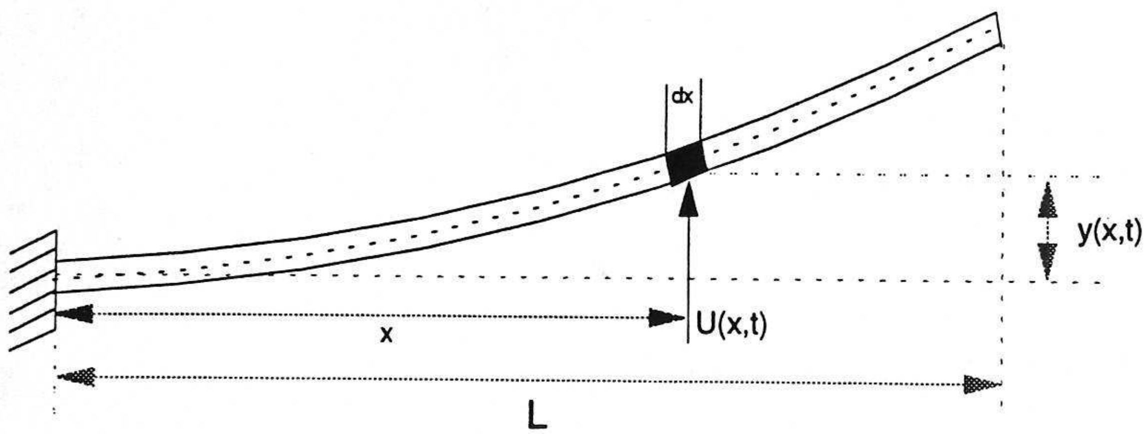
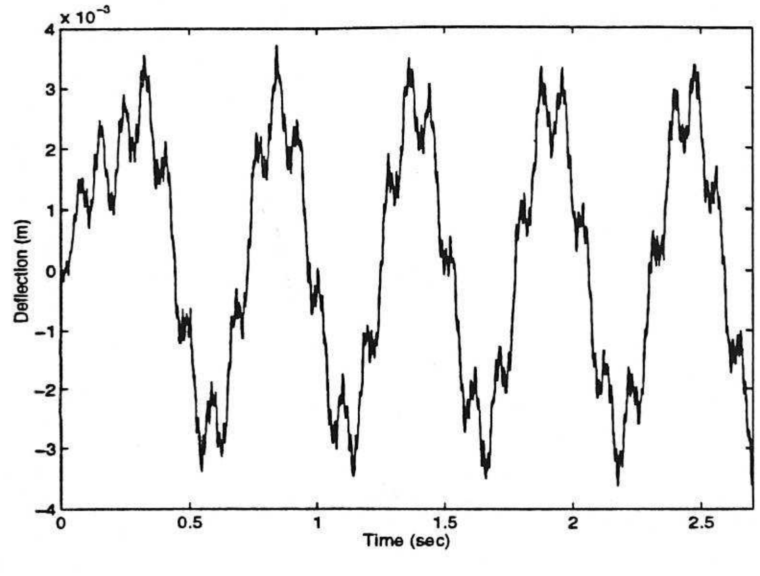


Figure 1: Schematic diagram of the cantilever beam system.



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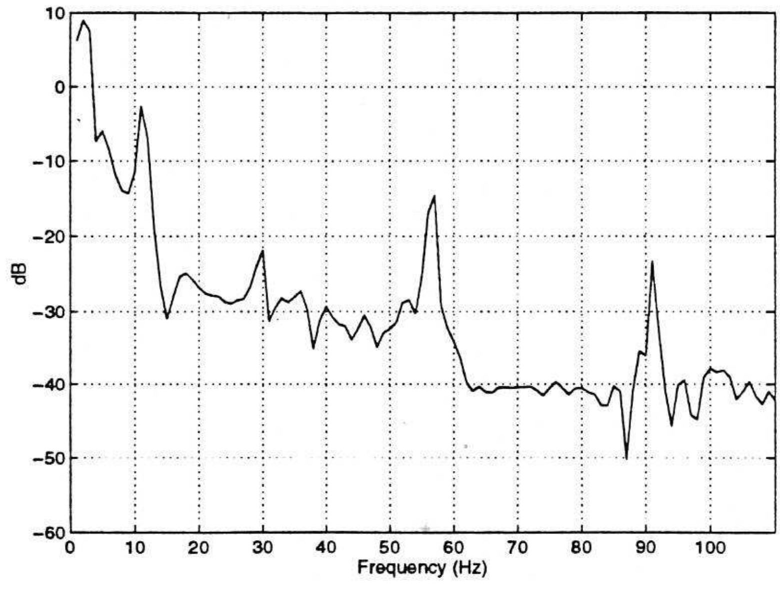
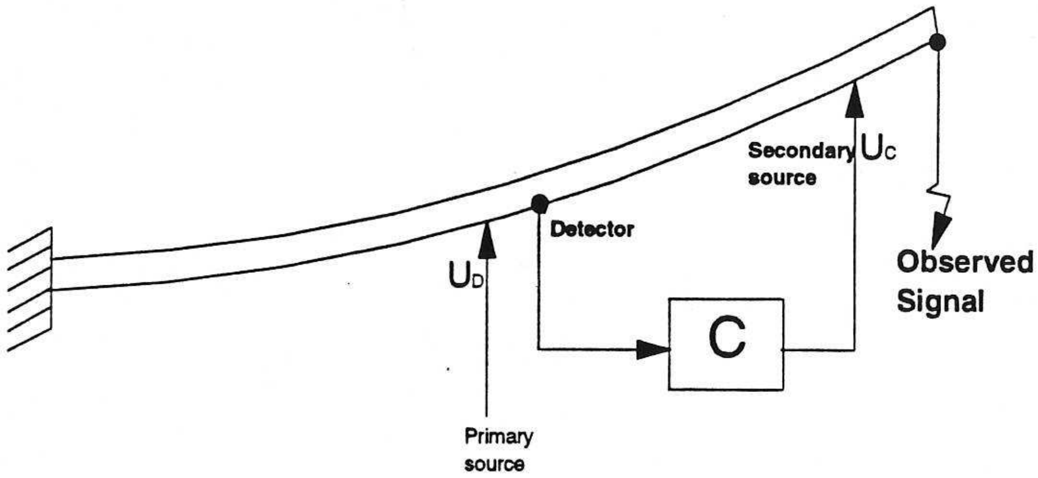


(b)

Figure 2: End-point response of the beam to $\pm 0.1N$ PRBS force;
(a) Time-domain.
(b) Autopower spectral density.



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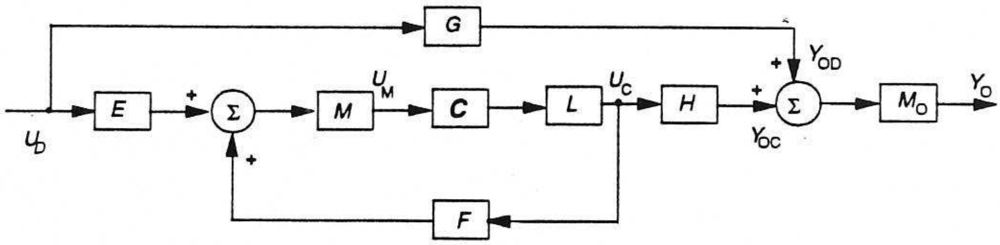


(b)

Figure 3: Active vibration control structure;
(a) Schematic diagram.
(b) Block diagram.

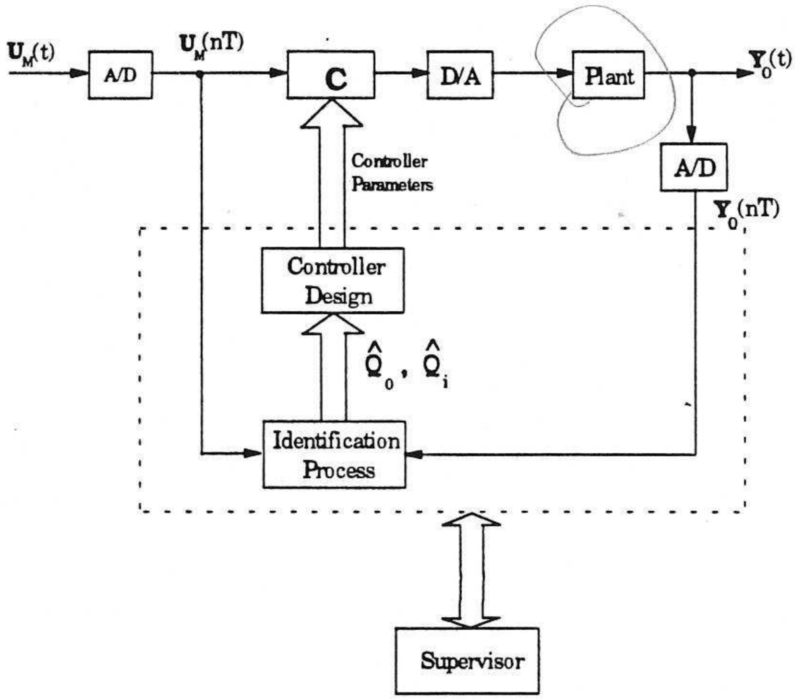
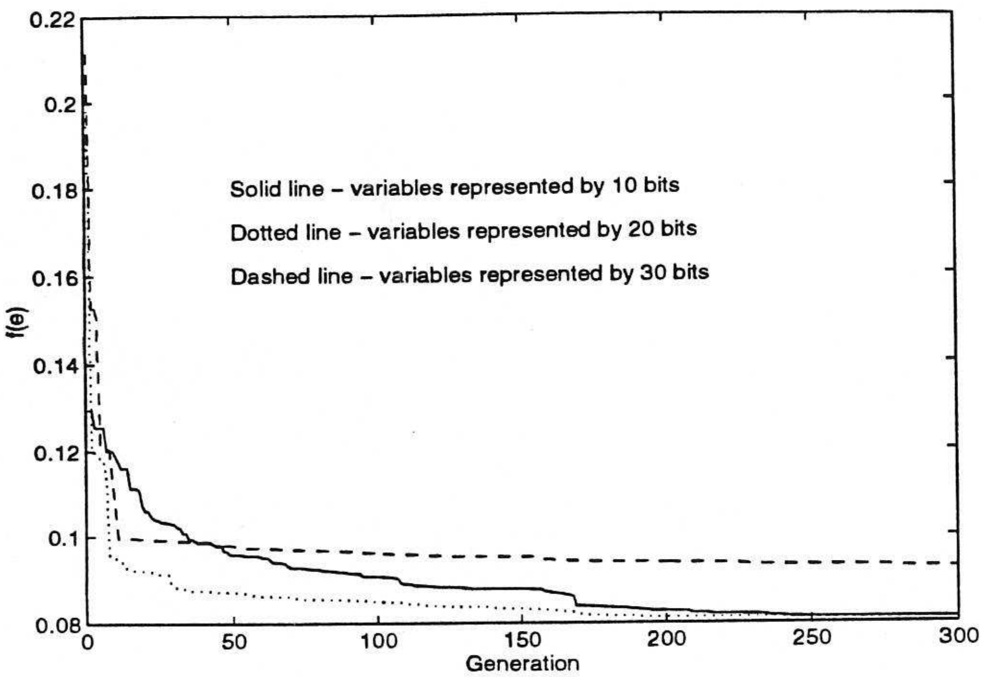
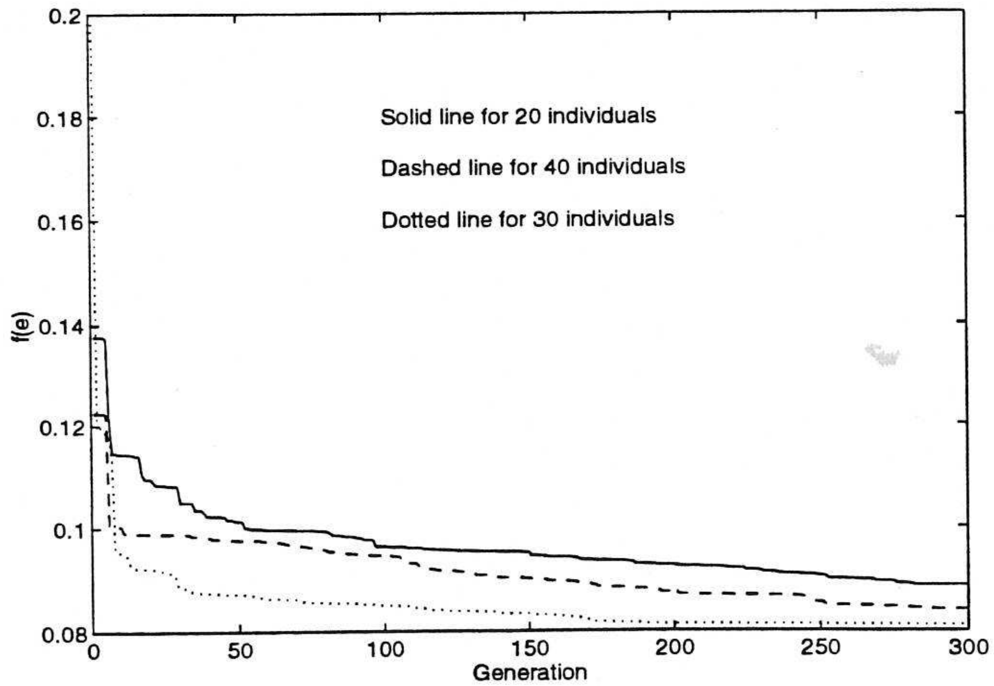


Figure 4: Self-tuning controller.



(a)



(b)

Figure 5: Variation of convergence of the fitness function;
(a) With representations.
(b) With individuals.

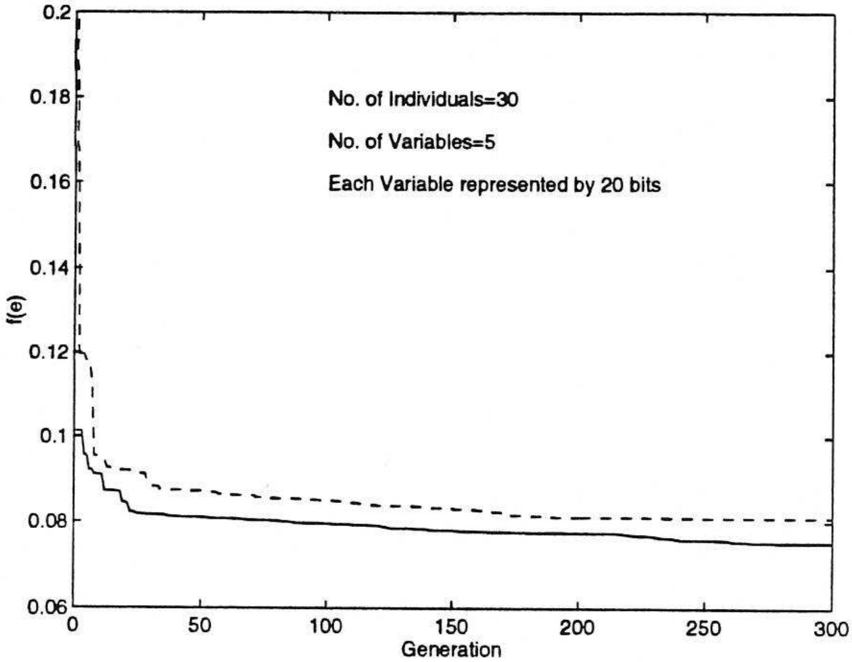


Figure 6: Convergence of the fitness function, for Q_0 (solid line) and Q_1 (dashed line).

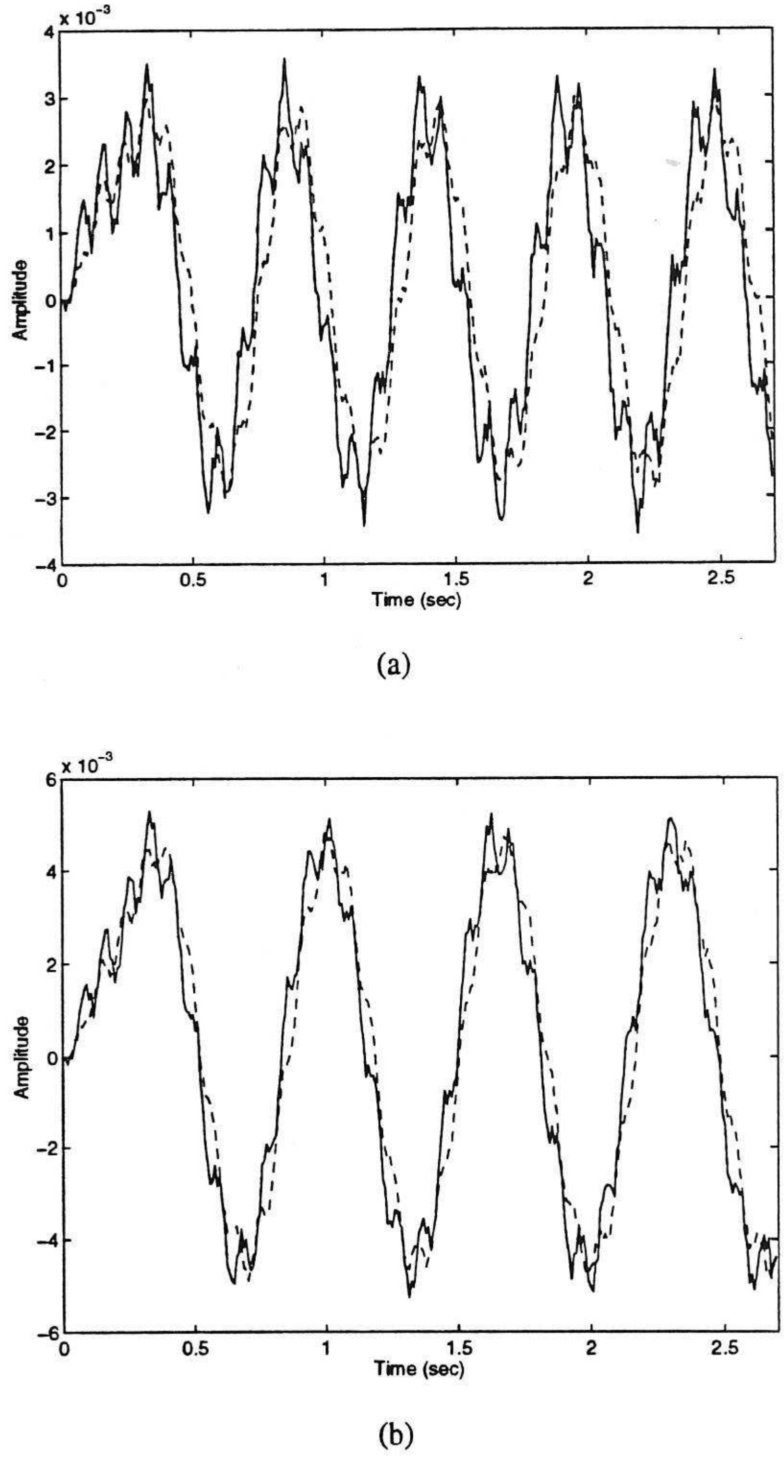
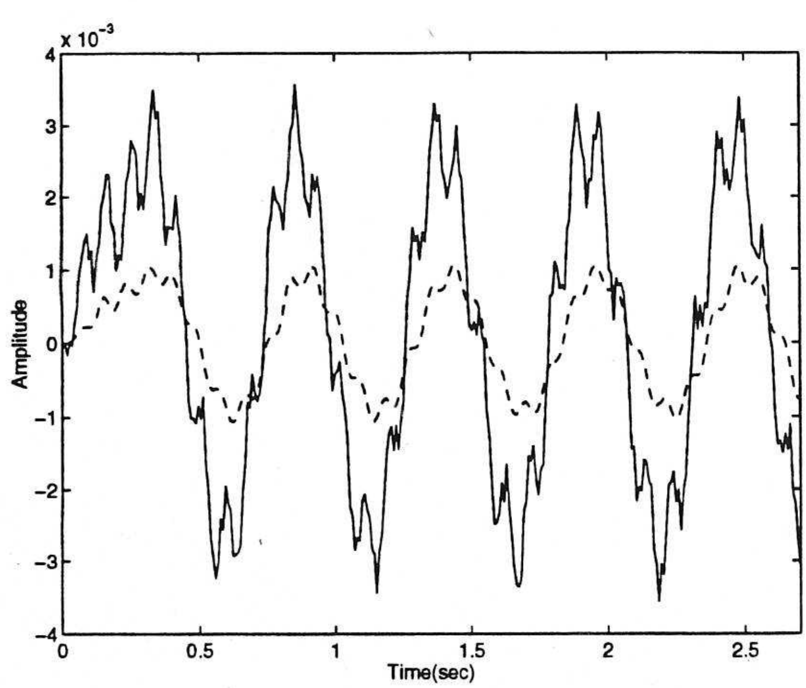
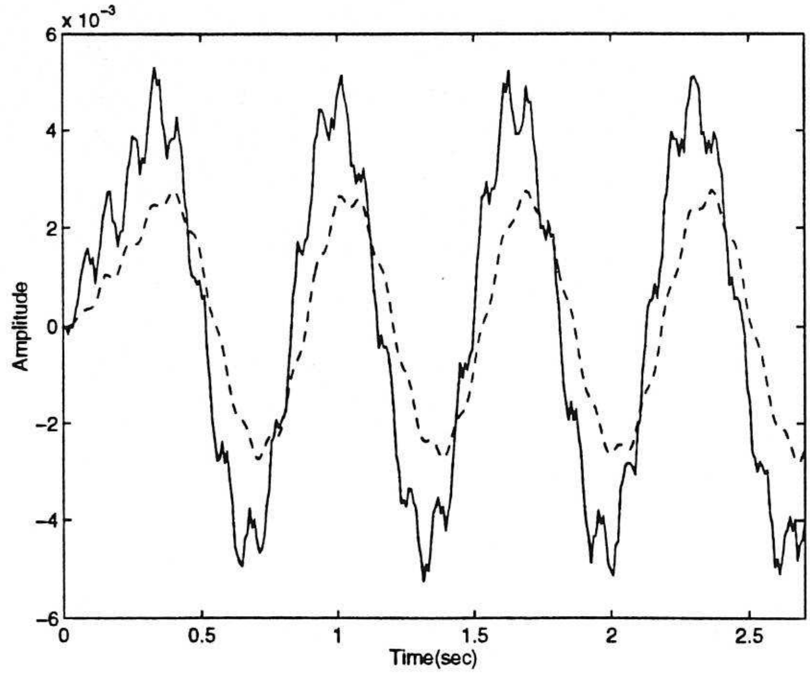


Figure 7: Performance of the GA based models;
(a) Desired (solid line) and estimated (dashed line) output for Q_0.
(b) Desired (solid line) and estimated (dashed line) output for Q_1.

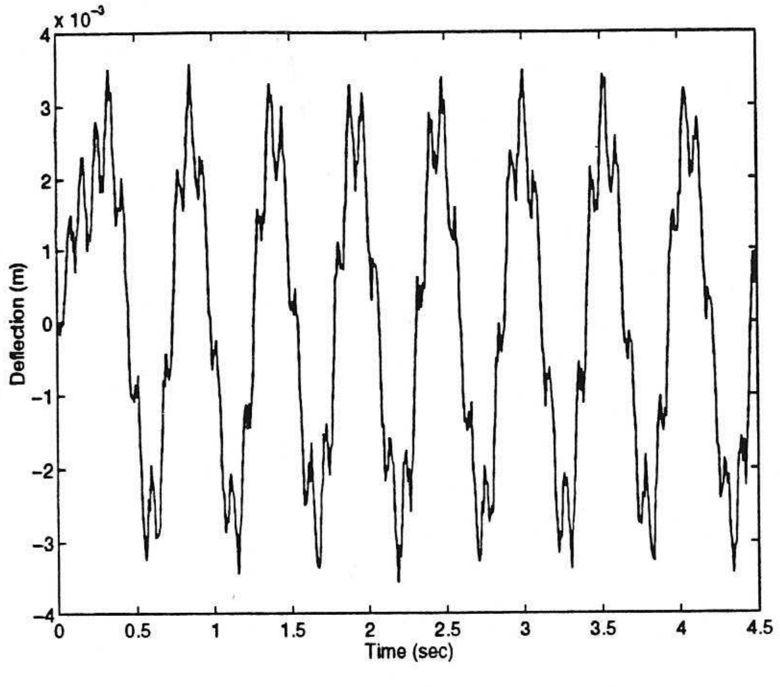


(a)

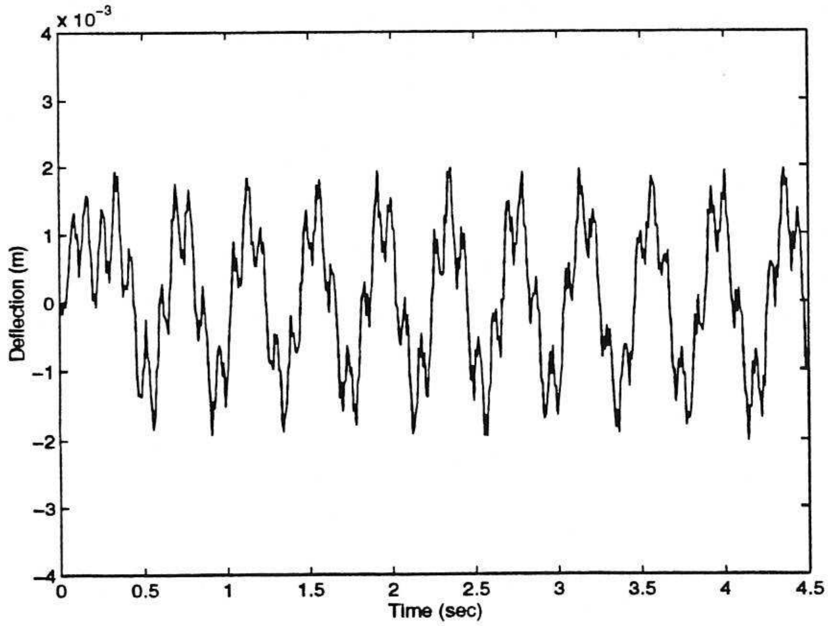


(b)

Figure 8: Performance of the RLS based models;
(a) Desired (solid line) and estimated (dashed line) output for Q_0.
(b) Desired (solid line) and estimated (dashed line) output for Q_1.

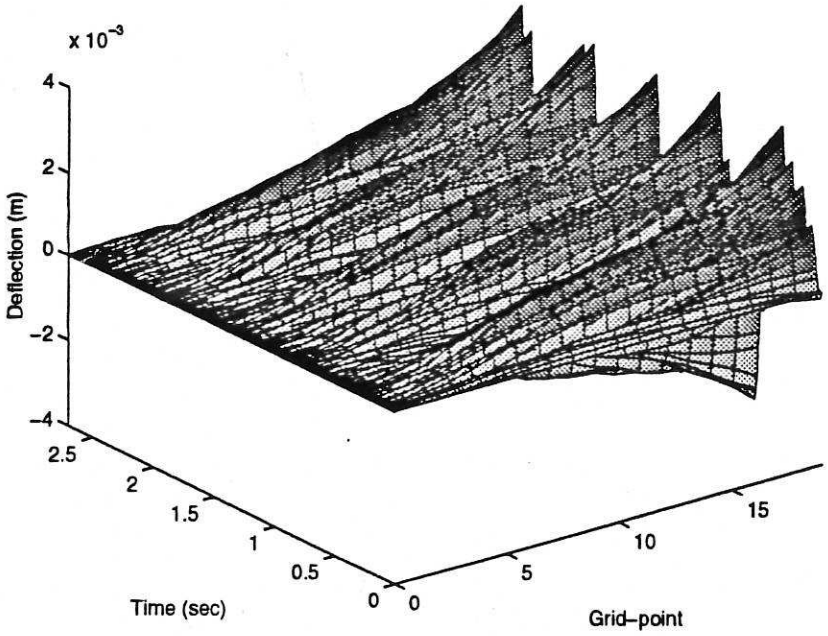


(a)

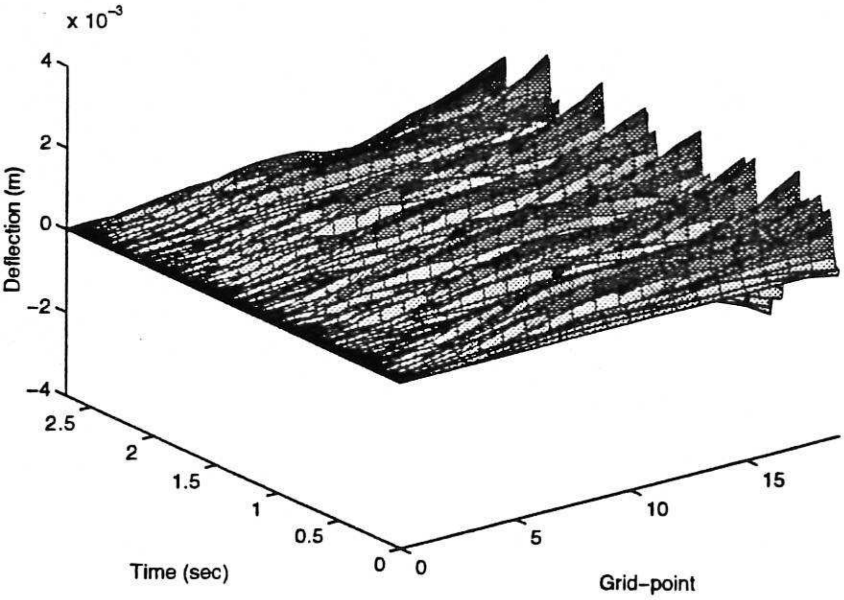


(b)

Figure 9: System response at the observation point with the GA based AVC system;
(a) Before cancellation.
(b) After cancellation.

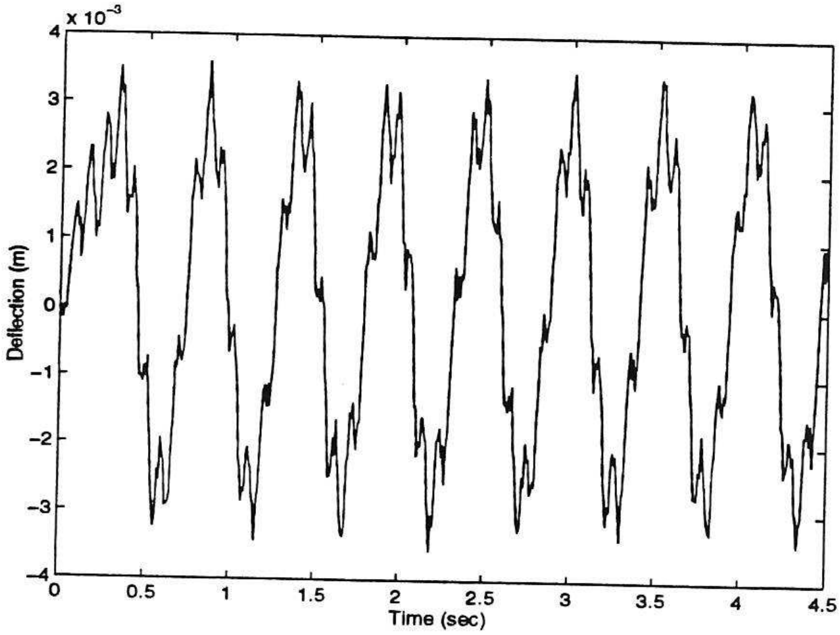


(a)

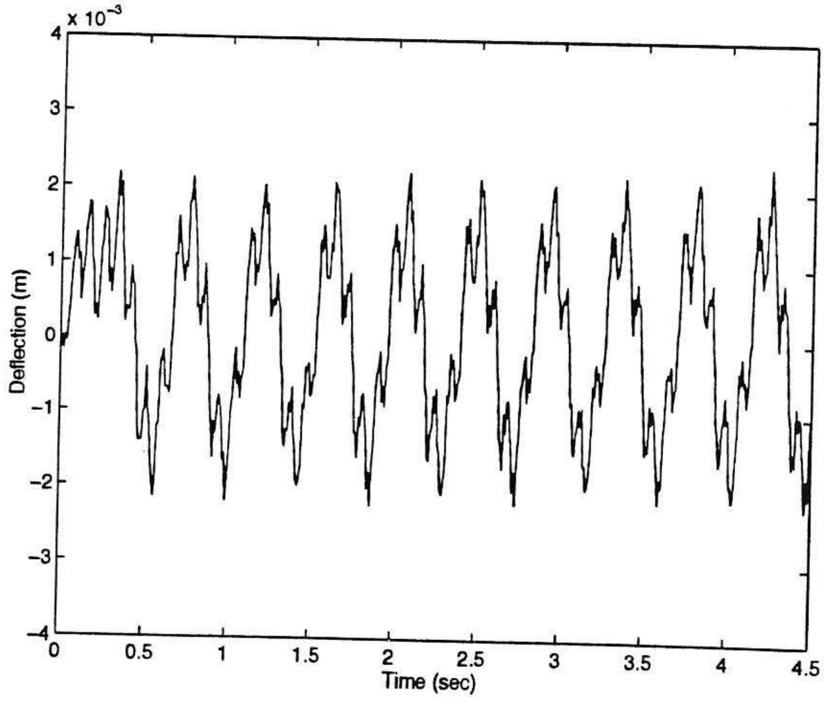


(b)

Figure 10: Beam fluctuation along its length with the GA based AVC system;
(a) Before cancellation.
(b) After cancellation.

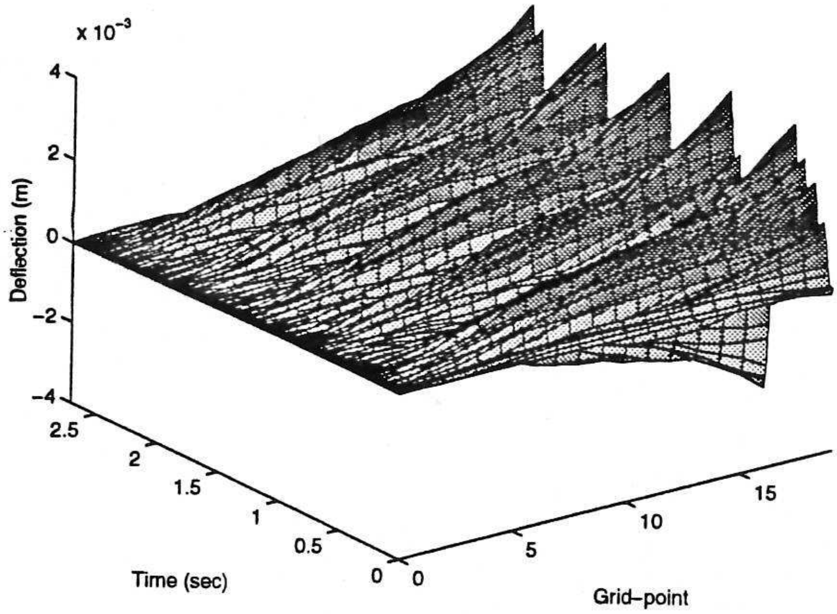


(a)

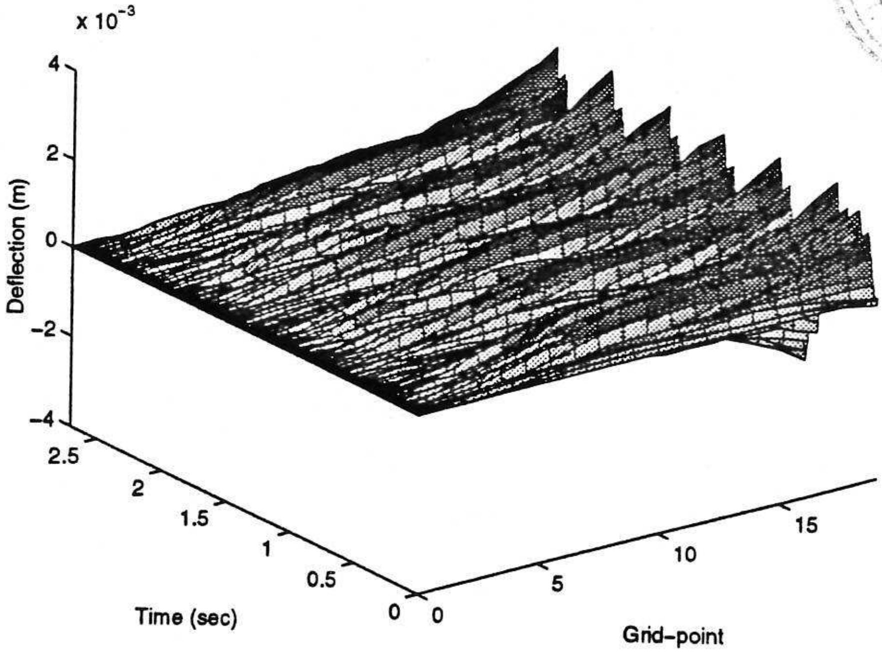


(b)

Figure 11: System response at the observation point with RLS based AVC system;
(a) Before cancellation.
(b) After cancellation.



(a)



(b)

Figure 12: Beam fluctuation along its length with the RLS based AVC system;
(a) Before cancellation.
(b) After cancellation.