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1 Abstract

Predictive controllers have found applications in a wide range of industrial processes. Two types of such controllers are generalized predictive control and deadbeat control. Recently, deadbeat control has been augmented to include an extended horizon. This modification, named deadbeat predictive control, retains the advantage of guaranteed stability and offers a novel way of control weighting. This paper presents an application of both predictive control techniques to vibration suppression of plate modes. Several system identification routines are presented. Both algorithms are outlined and shown to be useful in the suppression of plate vibrations. Experimental results are given and the algorithms are shown to be applicable to non-minimal phase systems.

2 Introduction

The control techniques described in this paper are in response to the need to reduce the level of unwanted acoustic energy radiated from a structure. In general, the structure is excited by broad band noise and the response is multimodal. Traditional methods of achieving active noise control are primarily focused on feed-forward techniques. In the literature, there is a large amount of information on such techniques along with impressive results.

To achieve feed-forward control, it is required that a coherent reference be available. It is also required that processing be done on this reference signal before it reaches the controlled location. Recent advances in microprocessors have increased the processing speed to the point where if a coherent reference

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is available, noise reduction can be achieved. However, it is not possible to use feed-forward when no such reference is available.

The feedback control approach does not need a reference to achieve active noise control, as the control signal is derived from the error sensor. The advances in microprocessor speed have made it possible to compute the control effort and apply it to the actuator within one sampling period. In designing control systems for this purpose, the algorithms must be fast enough to be implemented in real time. The control methods presented in this paper are computationally efficient.

In order to design the controller, an input/output model of the plant must be made. This model is the transfer function from the actuator to the error sensor. Typical methods of system identification are used to determine the parameters of this model. These methods include batch least squares and recursive least squares. If faster computation is desired, the projection algorithm¹ may be used at the expense of convergence speed. In general, any system identification technique may be used which will return an Auto-Regressive moving average model with eXogenous input (ARX) of the plant.

Based on the ARX model obtained using a system I.D. technique, a controller can be designed. Since the system identification can only return an approximation of the true plant under test, the controller must be robust against some parameter uncertainties. This implies that the control method chosen must have the ability to tolerate uncertainties to a certain degree without going unstable or suffering a large performance degradation.

Generalized Predictive Control (GPC) may be used to regulate a plant based on an identified model. This control technique may be tuned to the desired balance between performance and robustness. GPC also has the ability to regulate a non-minimal phase plant. However, the GPC algorithm suffers from the fact that there are too many parameters to adjust and it is not known ahead of time the best settings for these parameters. For this reason, the user may have to go through a lengthy trial and error process to properly tune the controller.

A novel technique for achieving active noise control of sound radiated from a structure is Deadbeat Predictive Control (DPC). In DPC there are only two integer parameters to adjust and stability is guaranteed. The DPC algorithm is similar to GPC in that it is a receding horizon controller, but differs from GPC in that it does not try to drive the error to zero immediately. By doing so, the problem of instability

resulting from the inversion of a non-minimal phase plant is always avoided. The performance of DPC is shown to be comparable to that of GPC.

While DPC and GPC are presented in this paper, in general any feedback technique may be a good candidate for vibration suppression. By extending the control and prediction horizons to very large values, the GPC solution approaches the linear quadratic regulator (LQR). Various methods of minimal variance control offer solutions to minimal phase plants. It is well known that collocation of sensors and actuators produces a minimal phase transfer function in continuous time. However, when in discrete time, this is shown to not always be the case. Various forms of proportional integral differential (PID) controllers have also been applied to achieve regulation. These controllers have a drawback in that they do not always approximate an optimal controller and collocation is necessary for reasonable robustness.

This paper presents the experimental results obtained by applying GPC and DPC to vibration suppression of an aluminum plate. Section 3 outlines the system identification technique and the model structure. Section 4 summarizes the GPC algorithm and section 5 summarizes the DPC algorithm. Section 6 describes the experimental setup and presents an off-line simulation based on the identified plant. Section 7 presents the experimental results for both GPC and DPC with a discussion following in section 8. Conclusions are given in section 9.

3 System Identification

For small displacements the input/output model of a structure can be reasonably represented by a linear finite difference model. If the plate displacement is large or the control effort becomes too great, the input/output map may become nonlinear. Even for nonlinear systems, the linear finite difference model can be shown to be a reasonable approximation over a small region of interest. For both GPC and DPC a finite difference model is used. The structure of this model, commonly called the Auto-Regressive moving average model with eXogenous input (ARX), is shown below.

$$y(k) = \alpha_1 y(k-1) + \alpha_2 y(k-2) + \dots + \alpha_p y(k-p) + \beta_0 u(k) + \beta_1 u(k-1) + \dots + \beta_p u(k-p)$$

It is the task of the system identification technique to produce estimates of β_j and α_j where $j = 1, 2, \dots, p$ and p is the ARX order. The batch least squares solution may be used to find the desired parameters. If it is

desired to obtain a solution on-line, then recursive least squares or any one of the numerous recursive techniques may be used. In general, any system identification technique can be used which will produce estimates of the α 's and β 's.

4 Generalized Predictive Control

The basic GPC algorithm was formulated by D. W. Clarke⁶ and is briefly presented here.

An ARX model is used to represent the input/output relationship for the system. In this model, y is the plant output and u is the control input. The disturbance is $e(t)$ and z^{-1} is the backwards shift operator. The ARX model can be simplified to become

$$A(z^{-1})y(t) = B(z^{-1})u(t-1) + e(t) \quad (1)$$

In order to reduce the effects of the disturbance on the system, a way of predicting the future plant outputs must be devised. It is desirable to express the future outputs as a linear combination of past plant outputs, past control efforts, and future control efforts. Once this is done, the future plant outputs and controls may be minimized for a given cost function. The following Diophantine equation is used to estimate the future plant outputs in an open loop fashion.

$$1 = A(z^{-1})E_j(z^{-1}) + z^j F_j(z^{-1}) \quad (2)$$

The integer N is the prediction horizon and $j = 1, 2, 3, \dots, N$. In the above equation, we have that

$$E_j(z^{-1}) = 1 + e_1 z^{-1} + e_2 z^{-2} + \dots + e_{N-1} z^{-N+1}$$

$$F_j(z^{-1}) = f_0 + f_1 z^{-1} + f_2 z^{-2} + \dots + f_{N-1} z^{-N+1}$$

For any given $A(z^{-1})$ and prediction horizon N , a unique set of j polynomials $E_j(z^{-1})$ and $F_j(z^{-1})$ can be found.

If the Eq. (1) is multiplied by $E_j(z^{-1})z^j$, one obtains

$$E_j(z^{-1})A(z^{-1})y(t+j) = E_j(z^{-1})B(z^{-1})u(t+j-1) + E_j(z^{-1})e(t+j)$$

Combining this with Eq. (2) yields

$$y(t+j) = E_j(z^{-1})B(z^{-1})u(t+j-1) + F_j(z^{-1})y(t) + E_j(z^{-1})e(t+j)$$

Since we are assuming that future noises can not be predicted, the best approximation is given by

$$y(t+j) = G_j(z^{-1})u(t+j-1) + F_j(z^{-1})y(t) \quad (3)$$

Here we have that $G_j(z^{-1}) = E_j(z^{-1})B(z^{-1})$. The above relationship gives the predicted output j steps ahead without requiring any knowledge of future plant outputs. We do, however, need to know future control efforts. Such future controls are determined by defining and minimizing a cost function.

Since Eq. (3) consists of future control efforts and past control and system outputs, it is advantageous to express it in a matrix form containing all j relationships. It is also desirable to separate what is known at the present time step from what is unknown, as this will aid in the cost function minimization. Consider the following matrix relationship

$$\mathbf{y} = \mathbf{G}\mathbf{u} + \mathbf{f}$$

where the $N \times 1$ vectors are

$$\mathbf{y} = [y(t+1), y(t+2), \dots, y(t+N)]^T$$

$$\mathbf{u} = [u(t), u(t+1), \dots, u(t+N-1)]^T$$

$$\mathbf{f} = [f(t+1), f(t+2), \dots, f(t+N)]^T$$

The vector \mathbf{y} contains the predicted plant responses, the vector \mathbf{u} contains the future control efforts yet to be determined, and the vector \mathbf{f} contains the combined known past controls and past plant outputs. The matrix \mathbf{G} is of dimension $N \times N$ and consist of the plant pulse response.

$$\mathbf{G} = \begin{bmatrix} g_0 & 0 & \dots & 0 \\ g_1 & g_0 & \dots & 0 \\ \vdots & & \ddots & \vdots \\ g_{N-1} & g_{N-2} & \dots & g_0 \end{bmatrix}$$

It is desired to find a vector \mathbf{u} which will minimize the vector \mathbf{y} . Consider the following cost function for a single input single output system

$$J = \sum_{j=1}^N (y(t+j))^2 + \sum_{j=1}^N \lambda (u(t+j-1))^2$$

Where the scalar λ is the control cost. Minimization of the cost function with respect to the vector \mathbf{u} results in

$$\mathbf{u} = -(\mathbf{G}^T\mathbf{G} + \lambda*\mathbf{I})^{-1}\mathbf{G}^T\mathbf{f}$$

The above equation returns a vector of future controls. In practice, the first control value is applied for the current time step and the rest are discarded. The above computations are repeated for each time step resulting in a new control value.

As can be found in the literature, the above algorithm has many variations. One way to achieve control of a non-minimal phase plant is to choose a value of NU smaller for the control vector \mathbf{u} than for the prediction horizon N, i.e. $NU < N$ where NU is the control horizon. This will also result in faster computations. The control effort may also be suppressed by increasing λ . It has been found that setting the control horizon smaller than the prediction horizon results in a controller which can regulate non-minimal phase plants with very little loss in performance. Generally, one should set the prediction horizon N at least equal to or greater than the system order p. The GPC algorithm thus has four possible parameters to adjust. The system order p, the prediction horizon N, the control horizon NU, and the control weight λ all must be chosen with care. As in most control systems, one has to balance performance with system stability and actuator saturation.

5 Deadbeat Predictive Control

The deadbeat predictive controller (DPC) offers excellent performance without the need to tune as many parameters as GPC. The basic algorithm is presented below and is based on the observable canonical form. Given the estimated values of the α 's and β 's, the system may be represented in observable canonical form.

$$\mathbf{Z}(k+1) = \mathbf{A}\mathbf{z}(k) + \mathbf{B}u(k)$$

$$y(k) = \mathbf{C}\mathbf{z}(k)$$

where

$$\mathbf{z}(k) = \begin{bmatrix} y(k) \\ z_1(k) \\ z_2(k) \\ \vdots \\ z_{p-1}(k) \end{bmatrix}, \quad \mathbf{A}_p = \begin{bmatrix} \alpha_1 & \mathbf{I} & 0 & \cdots & 0 \\ \alpha_2 & 0 & \mathbf{I} & \ddots & \vdots \\ \alpha_3 & 0 & 0 & \ddots & 0 \\ \vdots & \vdots & \vdots & \vdots & \mathbf{I} \\ \alpha_p & 0 & 0 & \cdots & 0 \end{bmatrix}, \quad \mathbf{B}_p = \begin{bmatrix} \beta_1 \\ \beta_2 \\ \beta_3 \\ \vdots \\ \beta_p \end{bmatrix}, \quad \mathbf{C}_p = [\mathbf{I} \ 0 \ 0 \ \dots \ 0]$$

If the controller is to be implemented in state space a state observer is needed. Once the observer is determined, the control effort for the present time step is given by

$$u(k) = Gz(k)$$

where G is the first r rows of

$$-[A_p^{q-1}B_p, \dots, A_pB_p, B_p]^+A_p$$

r is the number of inputs and q is the prediction horizon. The prediction horizon is chosen to be greater than or equal to the system order p. If q is set equal to p, then one obtains deadbeat control. Typically, q is set greater than p in order to limit the control effort so as not to saturate the actuator.

The DPC controller can also be implemented in polynomial form thereby eliminating the need for a state observer. The technique is shown below. The derivation can be found in the literature²⁵.

$$u(k) = F_1y(k-1) + F_2y(k-2) + \dots + F_p y(k-p) + H_1u(k-1) + H_2u(k-2) + \dots + H_p u(k-p)$$

The controller parameters are given by

$$F_1 = [g_1 \ g_2 \ \dots \ g_p] \begin{bmatrix} \alpha_1 \\ \alpha_2 \\ \vdots \\ \alpha_p \end{bmatrix}, \quad F_2 = [g_1 \ g_2 \ \dots \ g_{p-1}] \begin{bmatrix} \alpha_2 \\ \alpha_3 \\ \vdots \\ \alpha_p \end{bmatrix}, \quad \dots \quad F_p = g_1 \alpha_p$$

$$H_1 = [g_1 \ g_2 \ \dots \ g_p] \begin{bmatrix} \beta_1 \\ \beta_2 \\ \vdots \\ \beta_p \end{bmatrix}, \quad H_2 = [g_1 \ g_2 \ \dots \ g_{p-1}] \begin{bmatrix} \beta_2 \\ \beta_3 \\ \vdots \\ \beta_p \end{bmatrix}, \quad \dots \quad H_p = g_1 \beta_p$$

where $[g_1 \ g_2 \ g_3 \ \dots]$ consist of the appropriate number of columns of the G matrix defined above and the values of the α 's and β 's are those identified from the data. The formulation above eliminates the need for a state observer as it can compute the control effort based only on input and output measurements. The DPC will always be stable as long as $q \geq p$. This stability property will hold true for non-minimal phase system as well.

The DPC algorithm requires only two parameters to be adjusted, p the system order and q the prediction horizon. Both p and q are integers, so the tuning process is greatly simplified. The tuning of DPC

is a balance between performance and actuator saturation. If the control effort exceeds the limits of the actuator, then q may be increased to reduce the control signal. The value of p is typically chosen to be five or six times the number of significant modes of the structure. This allows for computational poles and zeros to improve the system identification results, i.e., it is well known that if there is a sufficient number of parameters to adjust in the system identification a Kalman filter will be approximated.

6 Experimental Setup

Figure 1 below shows the structure to be controlled by GPC or DPC.

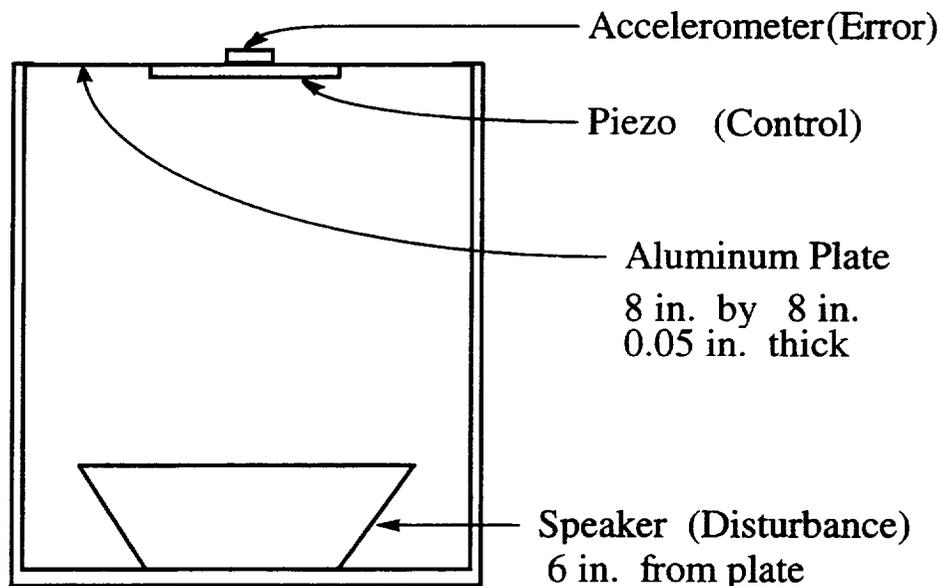


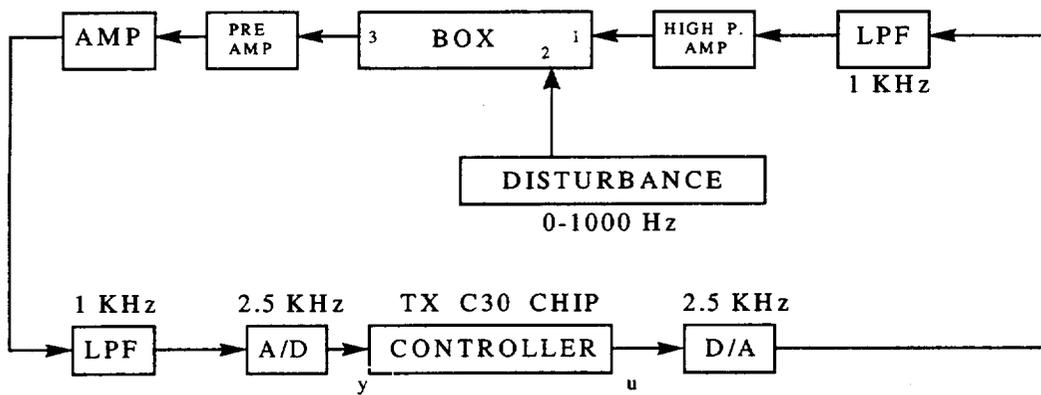
FIGURE 1 TEST BOX

The test box consist of an aluminum plate mounted on the top of a plexy glass box. The disturbance enters the plant through the loud speaker at the bottom of the box and causes the plate to vibrate, thereby radiating noise. A piezo-electric transducer is mounted under the plate as the control actuator. The error, plant output, is the signal read from the accelerometer. It is desired to reduce the amount of noise radiated from the plate, this is accomplished by reducing the vibration amplitude of the odd plate modes. Since the accelerometer is placed at the center of the plate, the plate motion at points other than the center is not detected. From a vibrations standpoint, this is equivalent to saying those modes with a

node at the accelerometer are not observable. This amounts to not suppressing, or possibly exciting, the even modes. Even though even modes are poor radiators, if it is desired to exercise control over them, an additional piezo accelerometer pair may be added. That may also improve the control authority over all modes. Since the control techniques presented can easily be extended to multi-input multi-output (MIMO) systems, this poses no problem.

It is well known that collocation of sensors and actuators results in a minimal phase system in continuous time. Even though both DPC and GPC can handle non-minimal phase systems, collocation results in improved performance. From a controls standpoint, this comes from the fact that the more minimal-phase like a system is, the easier it is to control. From a physical standpoint, this amounts to saying that the controller has a direct influence over the sensor output. Direct in this context means that the actuators efforts do not have to propagate through any of the structure to reach the sensor. Also, the actuator has the most control over the odd modes at the antinodes of the odd modes, likewise the greatest acceleration can be found at the antinode.

Figure 2 below shows the block diagram of the closed loop system.



1.) Control signal goes to PZT

2.) Disturbance enters the plant from the

3.) Error is picked up by accelerometer

LPF - low pass filter

HIGH P. AMP - high power amplifier

Sample rate is 2.5 KHz

FIGURE 2 BLOCK DIAGRAM OF CLOSED LOOP SYSTEM

This experimental setup was used to test the performance of both GPC and DPC. Band limited (0-1KHz) white noise was used as a disturbance input to excite the plate. The noise was generated by a white noise generator and then filtered through a four pole filter which had a three dB cut off of 1KHz. The aluminum plate had two odd modes in this bandwidth. One at around 300 Hz and the other at around 1 KHz. The control output and the accelerometer signal were also filtered with four pole filters set to 1 KHz. Because of the filters gradual roll off, the 1KHz mode was not greatly attenuated by the filters. The filters did, however, greatly suppress the higher odd modes.

When sampling any continuous time system, one must chose a sampling rate which is neither too fast nor too slow. If a continuous system is sampled too fast, a poor discrete time system identification results from the loss of frequency resolution. In addition to this, sampling too fast results in the placement of more zeros outside the unit circle which degrades the control performance. If sampling is performed too slowly, then the higher frequencies alias into the lower end of the frequency spectrum. Typically, experience has shown that a sampling rate between two to three times the highest frequency results in the best performance. After trying several different sampling rates, 2.5 KHz was found to yield reasonable performance for the experimental setup shown.

With a sample rate of 2.5 KHz, the input and output data were gathered for system identification. It is desired to find the transfer function between the points labeled u and y in Fig. 2. This was accomplished by input band limited white noise into the system at location u and measuring the resulting system response at location y. In performing the system identification in this manner, all system components, even the A/D and D/A, were modeled. Ten thousand input output points were collected and a batch least squares fix was made to a 12th order ARX model. The model order was chosen based on the number of modes and the fact that computational poles and zeros are needed for a good fit in the presence of disturbances. Several different orders were tried and 12 provided a good fit. A pole zero plot of the resulting system model is shown in Fig. 3 below.

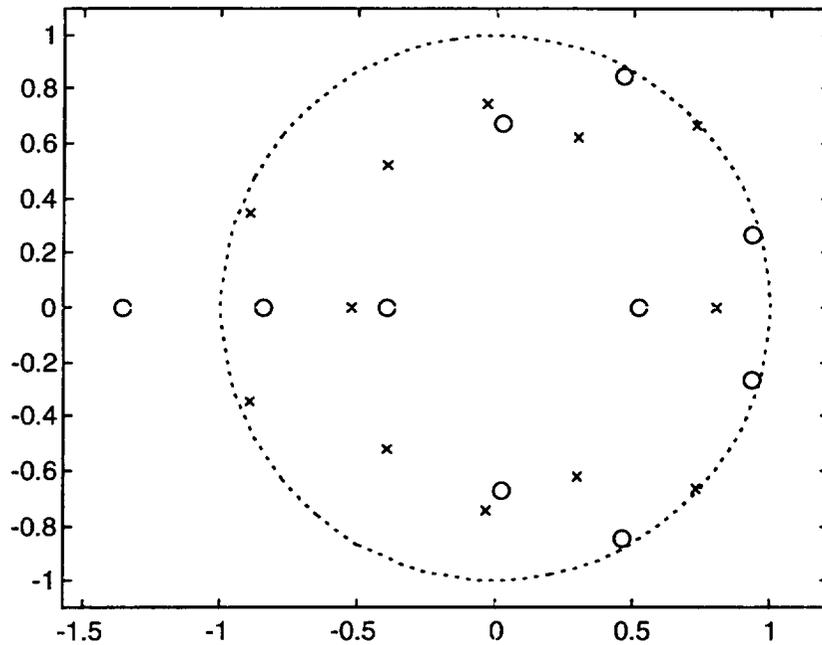


Figure 3 Pole Zero Plot of Transfer Function

As can be seen in Fig. 3 the dashed line represents the unit circle, the symbol x represents the poles, and the symbol o the zeros. There are two x's just inside the unit circle which result from the two lightly damped plate modes. Also note that there is a zero outside the unit circle. This non-minimal phase characteristic resulted from discretizing the minimal phase continuous time system.

After the system identification was complete, the GPC algorithm was used for controller design. Before implementing the controller, it is instructive to run a simulation and test the controller performance. The results are shown in Fig. 4.

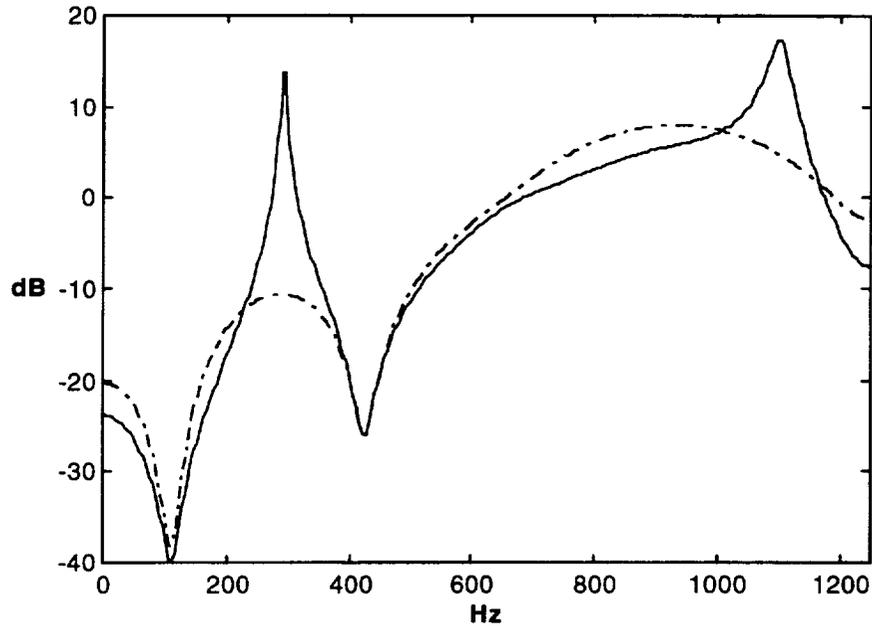


Figure 4 SIMULATION RESULTS

In Fig. 4, the dashed line is the bode plot magnitude of the closed-loop (controlled) system with the GPC controller and the solid line is the magnitude of the bode plot for the open-loop system. In both plots the identified model was used as the plant. As can be seen from Fig. 4, the two modes are present. When the loop is closed, we get about 22 dB reduction on the first mode and about 12 dB reduction on the second. There are some regions of the spectrum where the GPC controller is actually causing amplification. This results from the fact that the cost function was designed to minimize the overall system output and control effort in mind. Minimizing the plant output does not necessarily imply that the closed loop response will be reduced for all frequencies.

In designing the GPC controller, both control and prediction horizons were set to 20 and the control weight was set to 0.01. The horizon length was chosen to have a sufficient number of time steps beyond the system order (12th order) and the control penalty was adjusted to yield a stable closed-loop system. This adjusting of the horizons and control penalty was done both in the simulations and in the actual implementation. It was found that greater control could be exercised in the simulations which resulted in better disturbance rejection. This is not surprising since the plant model from which the controller was

designed was used in the simulations and the actual plant was used in the experimentation. Also, in the experiment noises are present whereas the simulations are noise free.

7 Experimental Results

Figure 5 shows the time history of the experimental output data. The plot includes the open and close-loop accelerometer signal. As in the simulations, the horizons were set to 20 and the control penalty to 0.01.

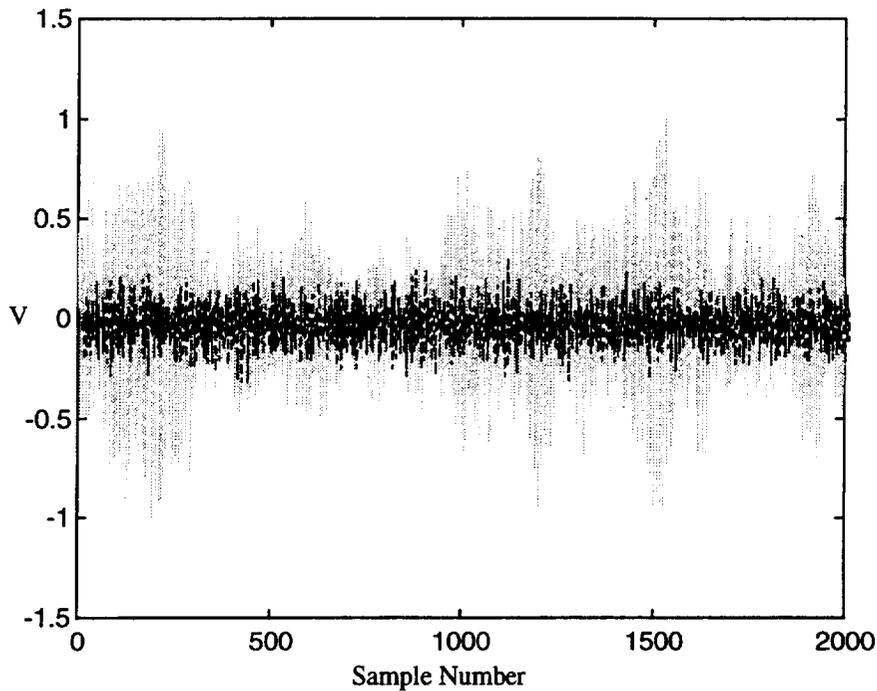


Figure 5 PLOT OF TIME HISTORY

In Fig. 5, the gray line is the open-loop accelerometer voltage and the darker line is the close-loop accelerometer voltage. Since the sample rate was set to 2.5 KHz, about one second of data is shown. It is obvious that some disturbance rejection is being obtained by closing the loop.

One way to judge how well a controller is performing is to examine the auto-correlation of the system output. The auto-correlation of the controlled and uncontrolled accelerometer output are plotted in Fig. 6.

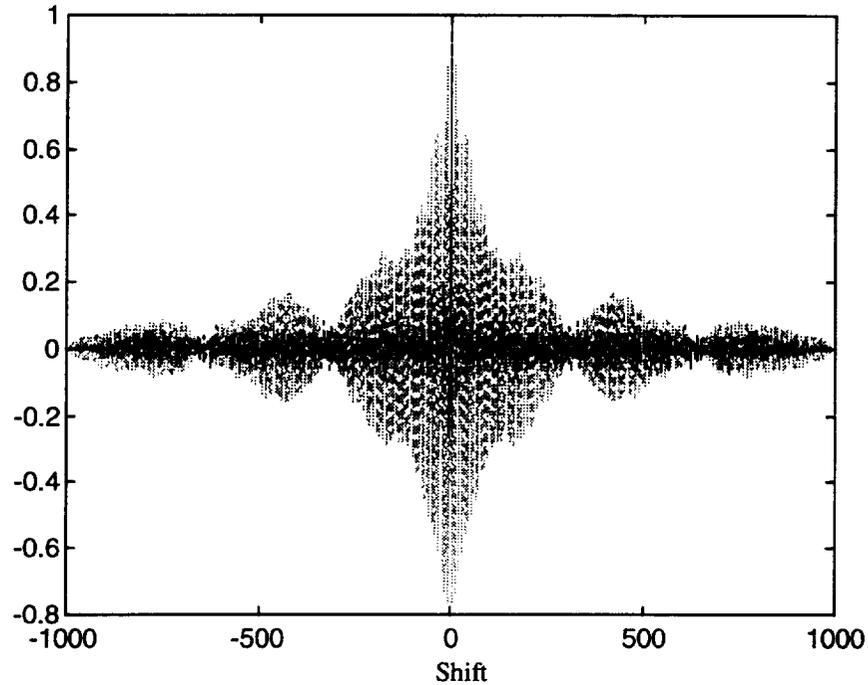


Figure 6 PLOT OF NORMALIZED AUTO-CORRELATION OF ACCELEROMETER OUTPUT

The open-loop auto-correlation is shown as gray while the close-loop is black. As can be seen in Fig. 6, the open-loop output has correlation in it. This correlation is due to the presence of the two modes at 300 Hz and 1 KHz. In theory, it is known that applying feedback control to the plant will remove the correlation from the output. Feedback control can only remove correlation from the plant response. It cannot reduce the level of uncorrelated noise at the sensor output. As can be seen from Fig. 6, the correlation has been mostly removed.

The Fourier transform of the auto-correlation will give the spectrum. The spectra of the open and close-loop systems are shown in Fig. 7. Once again GPC was used with the horizons set to 20 and the control penalty to 0.01. The sampling rate is 2.5 KHz.

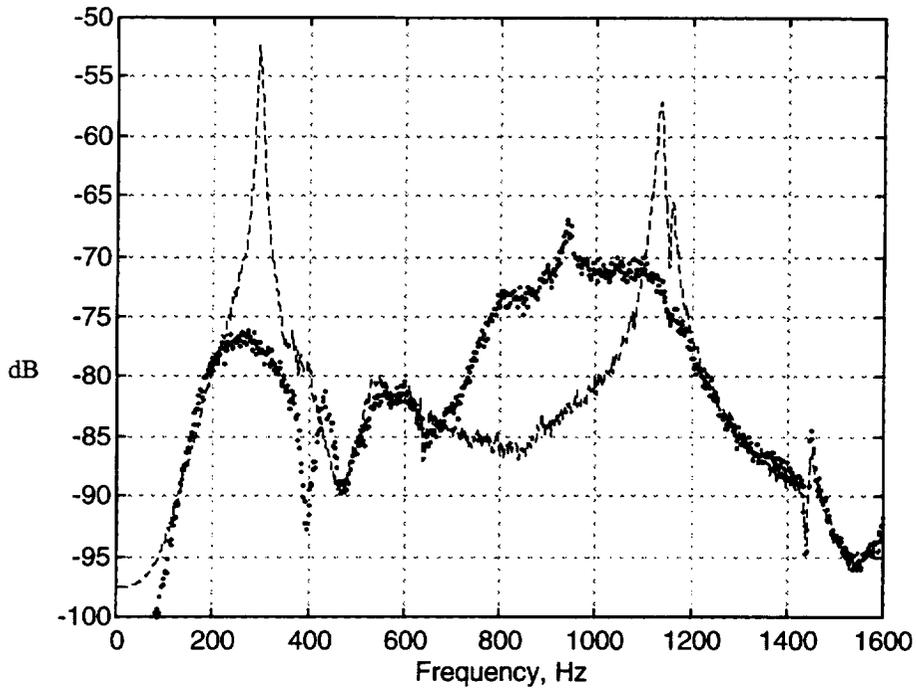


Figure 7 GENERALIZED PREDICTIVE CONTROL

In Fig. 7, the dashed line is the spectrum of the accelerometer output without control and the dotted line is the output with control. The result is similar to that shown in Fig. 4. In Fig. 7, the vertical axis is not calibrated and is used only to show the close-loop result relative to the open-loop result. At the first mode, around 300 Hz, we see an approximate reduction of around 22 dB while at the second mode we see a reduction of around 10 dB. This is in close agreement to the simulation results. Some of the differences between Fig. 4 and 7 can be accounted for by uncertainties in the identified ARX model parameters and noises in the experiment.

Deadbeat Predictive Control was also tested in the same setup. The spectrum results are shown in Fig. 8.

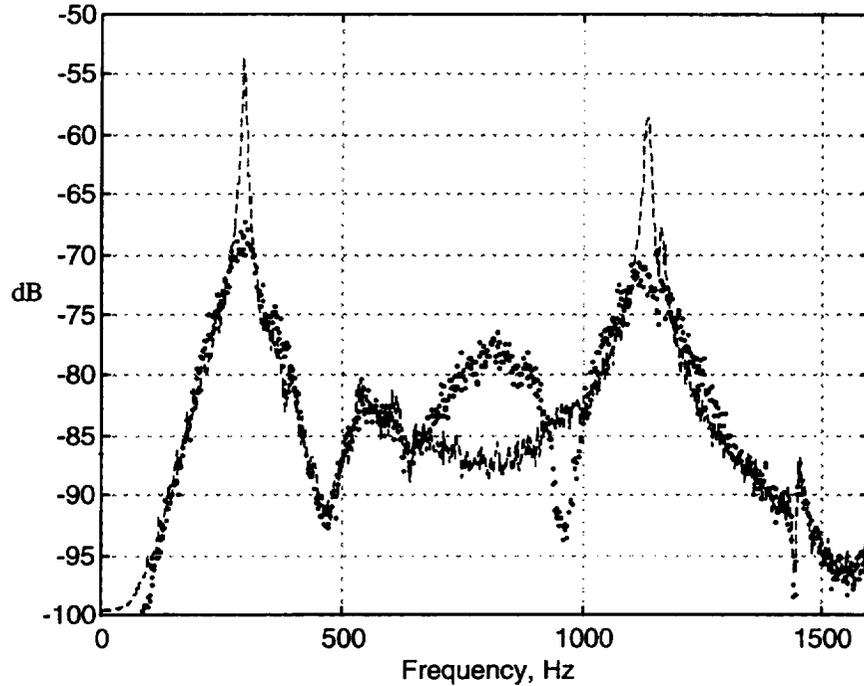


Figure 8 DEADBEAT PREDICTIVE CONTROL

The dashed line is the open-loop accelerometer output and the dotted line is the close-loop. From Fig. 8 both modes are lowered to around the same level. The mode at 300 Hz has an approximate reduction of 15 dB while the 1 KHz mode is reduced by around 13 dB. As in the GPC spectrum, the vertical scale is used only for comparison purposes. The fact that DPC lowers the peaks in the spectrum to approximately equal level is a result of not having a control weight. In tuning the DPC controller, one has to adjust only one integer parameter after the order of the system has been determined. This integer parameter, the control horizon, was adjusted to give the best reduction without saturating the actuator.

For the system order of $p = 10$ which was used, the control horizon was set to 12, i.e. $p + pc = 12$. Since the control horizon is always chosen to be greater than or equal to the system order, the tuning of DPC was found to be a simple task.

The performance of the DPC algorithm was further tested by increasing the bandwidth. The results are shown in Fig. 9.

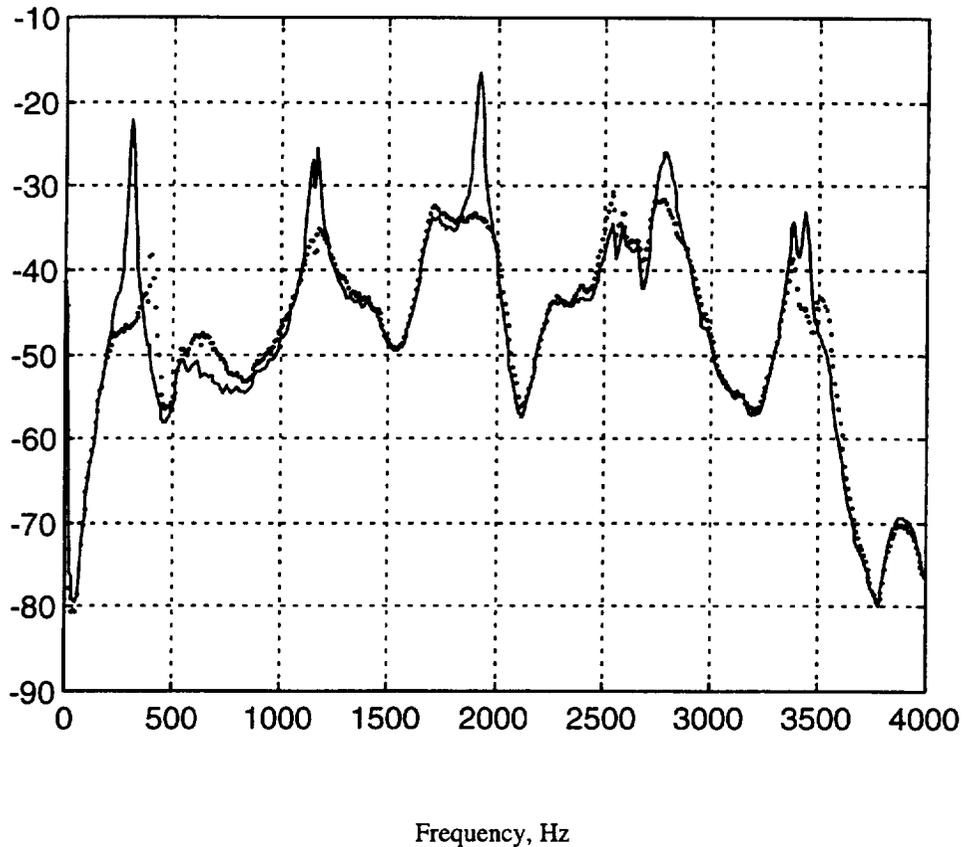


Figure 9 Deadbeat Predictive Control With Large Bandwidth

Fig. 9 shows that deadbeat predictive control can be used to suppress the vibrations of a plate over a wide bandwidth. As can be seen in the figure, five modes are attenuated. This was accomplished by increasing the filter bandwidths to 3150 Hz, the sampling rate to 12 kHz, and the system order to 18.

8 Discussion

The LQR solution has been proven to be the optimal solution for the regulation of a linear plant¹¹. If one extends both control and prediction horizons to infinity, the GPC becomes the LQR solution. As can be seen from Fig. 6, the finite horizon solution has removed all noticeable correlation, so there is very little room for improvement regardless of the feedback technique chosen.

By using a finite horizon technique, we have a solution which offers the possibility of being derived on-line in an adaptive controller. In this present study, both the system identification and the

controller design were done off line. Because of the computational speed of GPC or DPC, it is believed that the system identification can be updated, a new controller computed, and a new control effort applied every time step. This will create a controller which can regulate a time varying plant.

Regulating the vibration of a structure often means the control of a non-minimal phase system, as can be seen in Fig. 3. If the system identification was perfect, the DPC solution in all cases is guaranteed to be stable. The GPC solution offers no stability guarantee and must be carefully tuned to produce an acceptable solution without going unstable. Because all system identifications will have some uncertainty, both algorithms require tuning. In tuning DPC, one integer value is adjusted and GPC requires the adjustment of two integer values and one real positive value. These are the horizons and control weighting, respectively.

In addition to instability, actuator saturation must be avoided. In this study, the actuator limit is the 3 volt cutoff of the D/A card. For the GPC algorithm the control effort can be limited by increasing the horizon lengths or by increasing the control penalty. For the DPC solution the control effort is limited by increasing the control horizon. If the DPC control horizon is set to the system order, a deadbeat controller is realized. If the control horizon is greater than the system order a minimal energy solution is obtained.

9 Conclusions

Predictive control techniques have been shown to offer a solution to suppressing the vibrations of a structure. Most researchers in active noise control have relied on a coherent reference and employed feedforward control techniques. While feedforward techniques are in general the most effective, they assume that a reference is available and that it can be processed fast enough to cancel the disturbance at the area of interest. When such requirements cannot be met, feedback control may be used to offer some attenuation.

In conclusion, it was the purpose of this study to demonstrate the possibilities of using feedback control as a method of active noise control. By canceling out the odd vibration modes, the amount of acoustic energy radiated will be significantly reduced. Improvements may be made in noise reduction by optimal sensor and actuator locations on the structure along with incorporating a knowledge of which modes are producing the most acoustic energy at the area of interest.

This study demonstrated the use of two receding finite horizon controllers, generalized predictive control and deadbeat predictive control. These techniques were chosen because of their fast computational speed which offers extendibility to adaptive control. While generalized predictive control and deadbeat predictive control are not the optimal solution, i.e. linear quadratic regulator (LQR), they may come very close to the optimal solution without the computational burden of solving a Riccati equation.

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13. ABSTRACT (Maximum 200 words) Predictive controllers have found applications in a wide range of industrial processes. Two types of such controllers are generalized predictive control and deadbeat control. Recently, deadbeat control has been augmented to include an extended horizon. This modification, named deadbeat predictive control, retains the advantage of guaranteed stability and offers a novel way of control weighting. This paper presents an application of both predictive control techniques to vibration suppression of plate modes. Several system identification routines are presented. Both algorithms are outlined and shown to be useful in the suppression of plate vibrations. Experimental results are given and the algorithms are shown to be applicable to non-minimal phase systems.				
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