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Modelling and Open-Loop Control of a Single-Link Flexible Manipulator with Genetic Algorithms

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ABSTRACT
An open-loop control strategy for vibration suppression of a flexible manipulator system using genetic algorithms is presented in this paper. This consists of developing suitable forcing functions so that the dominant vibration modes of the system are not excited and hence the system vibration is reduced. The method requires that the vibration modes of the system be determined very precisely. Genetic algorithms (GAs) are used for this purpose. Low-pass and band-stop (elliptic type) filtered bang-bang torque inputs are accordingly developed on the basis of the identified vibration modes. The filtered torque inputs thus developed are applied to the system in an open-loop configuration and their performances in suppressing structural vibrations of the system are assessed in comparison to a bang-bang torque input. A comparative study of the low-pass and band-stop filtered torque inputs in suppressing the system vibrations are also presented and discussed.

Keywords: Filtered torque input, flexible manipulator, genetic algorithms, open-loop control, vibration suppression.

1. INTRODUCTION

The increased utilisation of robotic manipulators in various applications has been motivated by the requirements of industrial automation in recent years. Among the two types of manipulators, namely, rigid and flexible, attention is focused more on flexible manipulators as they can be operated at high speeds and are capable of handling larger payloads as compared to rigid manipulators with the same actuator capabilities. Moreover, flexible manipulators offer several other advantages. These include: light weight, lower energy consumption, safer operation due to reduced inertia, smaller actuator requirement, low mounting strength requirement, low rigidity requirement and less bulky design (Menq and Chen, 1988). Due to such advantages flexible manipulators are extensively being used in various applications, including space exploration and nuclear plants. However, system vibration arising from the structural flexibility is a major constraint in realising the advantages of flexible manipulators. Accordingly, control of flexible manipulators has been a challenge for researchers and engineers. A number of techniques have been proposed and implemented to control structural vibration of flexible manipulators. One of the popular methods involves shaping the input torque with filters to suppress energy input at the dominant frequency modes and accordingly reduce system vibrations (Tokhi and Azad, 1995; Poerwanto, 1998). This method requires accurate detection of the vibration modes through appropriate identification and modelling techniques.

A genetic algorithm (GA) operates on a population of potential solutions by applying the natural evolutionary process, i.e., principles of survival of the fittest, to produce better and better approximations to a solution and as such it is flexible and parallel in nature. GAs constitute global and data independent search techniques. These attractive features have made GAs easy to realise, implement and use in solving practical problems. Other attractive features of a GA include the following (Chipperfield et al., 1994):

- It uses discontinuous objective functions
- It offers multiple solutions to multi-mode problems
- It does not require derivative information or other auxiliary knowledge
- It uses probabilistic transition rules, not deterministic ones
- It works on an encoding of the parameter set rather than the parameter set itself
- It provides a number of potential solutions and the choice of final solution is left to the user.

Since their introduction by Holland (1975) as evolutionary algorithms, there has been growing interest among scientists and engineers in the use of GAs in various applications (Man and Tang, 1996). The use of GAs in identification and control applications is widely reported in the literature. Kristinsson and Dumont (1992) applied a GA for purposes of system identification and control. GAs have been used for non-linear model term selection by Fonseca et al. (1993). In this work, the GA was employed as an alternative to orthogonal least-square regression (Chen et al., 1991) to find a smaller set of non-linear model terms from a broader set of possible terms. Caponetto et al. (1995) have also addressed application of GAs in identification. They have utilised GAs to determine the parameters of the Chua's oscillator, assuming that the temporal series of the state variables of another Chua's oscillator are known. There are a number of cases where GAs have been used in robot path planning and control applications. Davidor (1991) has addressed a GA-based trajectory generation of a three-arm configuration robot. Alander (1991) addressed the feasibility of using GAs to solve complex robot problems, such as, task planning, adaptation, error detection and recovery to create a flexible robot control system. Michalewicz (1996) utilised the order-based coding in an evolutionary navigator where a chromosome is represented as an ordered list of path nodes. Ge et al. (1996) applied a simple and efficient decimal GA optimisation procedure to tune and optimise the performance of a Lyapunov-based robust controller for a single-link flexible robot. Evolutionary fuzzy control of a flexible link has been addressed by Akberzadeh-T et al. (1997). However, it is evident from the literature that little has been reported on the use of GA-based optimisation mechanism for modelling and vibration control of flexible robot arms.

This paper presents an investigation into the use of GAs from a system identification point of view in designing a controller based on the plant model to suppress the vibrations of a single-link flexible manipulator. This is realised by minimising the prediction error of the actual plant output and the model output. Different identification algorithms such as least mean square (LMS), recursive least squares (RLS) and neural networks have previously been used to model the system and to obtain the dominant vibration modes (Tokhi and Azad 1995, Poerwanto 1998, Tokhi et al., 1999). The various attractive features of GAs as described earlier motivate utilisation of a GA for this purpose. In this investigation elliptic type low-pass and band-stop filtered bang-bang torque inputs are developed on the basis of the vibration modes detected through GA-based modelling technique and applied to the system to reduce the motion-induced system vibrations. The paper is organised as follows: Section 2 describes the system, Sections 3 and 4 present descriptions of GAs and GA-based modelling respectively. The open-loop control strategy is described in Section 5. Section 6 presents results and implementations. A comparative assessment of the results is presented in Section 7 and the paper is concluded in Section 8.

2. THE FLEXIBLE MANIPULATOR SYSTEM

A schematic diagram of the single-link flexible manipulator considered in this work is described in Figure 1, where I_h represents the hub inertia of the manipulator. A payload mass Mp with its associated inertia I_p is attached to the end point. A control torque $\tau(t)$ is applied at the hub by an actuator motor. The angular displacement of the manipulator, in moving in the POQ plane, is denoted by $\theta(t)$. The manipulator is assumed to be stiff in vertical bending and torsion, thus allowing it to vibrate (be flexible) dominantly in the horizontal direction (POQ plane).

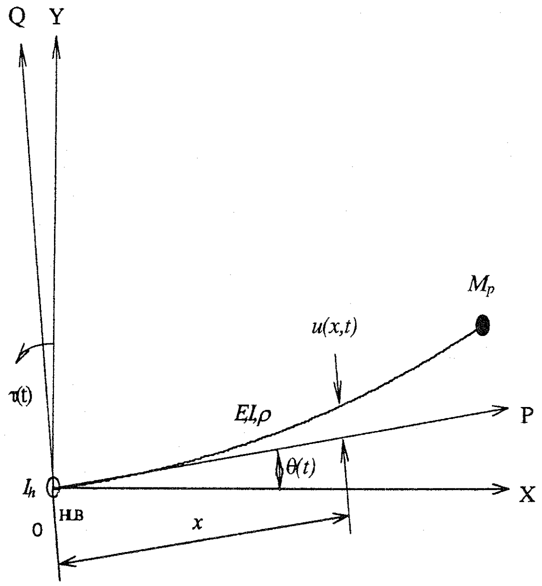


Figure 1. The flexible manipulator system

For an angular displacement θ and an elastic deflection u the total (net) displacement $y(x,t)$ of a point along the manipulator at a distance x from the hub can be described as a function of both the rigid body motion $\theta(t)$ and the elastic deflection $u(x,t)$ measured from the line OX;

$$y(x,t) = x\theta(t) + u(x,t) \tag{1}$$

It follows from equation (1) that in such a system, the control action is to take account of both the rigid body motion and the elastic motion. The main concern in this paper is suppression of the elastic motion (vibration).

Table 1.
Physical parameters of the flexible manipulator

Parameter	Value
Length	960.0 mm
Width	19.008 mm
Thickness	3.2004 mm
Mass density per unit volume	2710 kgm^{-3}
Second moment of inertia, I	5.1924×10^{-11} m^4
Young modulus, E	71×10^9 Nm^{-2}
Moment of inertia, I_b	0.04862 kgm^2
Hub inertia, I_h	5.86×10^{-4} kgm^2

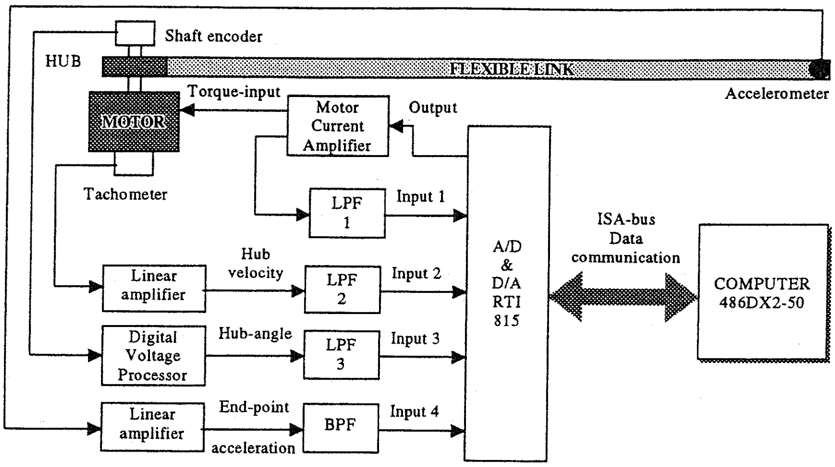


Figure 2. Schematic diagram of the experimental rig

The experimental rig constituting the flexible manipulator system is shown in Figure 2. This comprises three main parts: the flexible arm and driving motor with amplifier, the measuring devices and data processing element including a computer and interface devices. The flexible arm is of a thin aluminium alloy type with physical parameters given in Table I.

The rig is equipped with a U9M4AT type printed circuit motor driving the flexible manipulator (Azad, 1994). This type of motor gives high acceleration. It has a very low inductance and the torque is almost constant throughout its speed range. The motor drive amplifier used is the LA5600 type manufactured by Electro-Craft Corporation (Azad, 1994). This is a bi-directional drive amplifier and delivers a current proportional to the input voltage. It serves as a velocity/position controller as well as a motor driver. This amplifier has a four clamp facility, which can be used to limit or restrict the function of the amplifier and consequently of the entire system to accommodate various application requirements (Azad, 1994, Poerwanto, 1998).

The measuring devices incorporated into the system include a shaft encoder, a tachometer, an accelerometer and strain gauges. The shaft encoder, tachometer and accelerometer are essentially utilised in this work. The shaft encoder is used for measuring the hub angle of the manipulator. The tachometer is used for measurement of the hub velocity and the accelerometer, located at the end-point of the flexible arm, is used for measuring the end-point acceleration.

An IBM-PC compatible based on 486DX2-50MHz CPU, with 20 Mbytes of dynamic and 540 Mbytes of static memory is used with the experimental rig. Data acquisition and control are accomplished through the utilisation of an RTI-815 I/O board. The board contains a single 12-bit A/D converter with a conversion time of 25μ sec. The board also contains two independent voltage output channels, each with its own 12-bit D/A converter, which can produce an output of 0 to +10V or $\pm$ 10V. The output settling time is 20μ sec for full-scale step changes. The board also provides an 8-bit, eight channel non-latching parallel digital input port and an 8-bit latching parallel digital output port. The board is mapped into the microcomputer's I/O channel structure as a block of 16 consecutive bytes, addressable on any unoccupied 16-byte boundary from address 200H to 3FFH.

3. GENETIC ALGORITHMS-OPERATING PRINCIPLES

From an operational perspective, a GA comprises two basis elements-a set of individuals, i.e., potential solutions (the population) and a set of biologically inspired operators active over the population. A new set of approximations/solutions is created at each generation, by the process of selecting individuals according to their level of fitness in the problem domain and breeding them together using the operators. 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 (Chipperfield and Fleming, 1994). Individuals or current approximations are encoded as strings (typically represented in binary), chromosomes, and then the most promising strings are manipulated using the GA operators for better and better approximation to a solution. The operating mechanism of a GA can be described through the following stages:

1. Creation of an initial set of potential solutions (population) as strings.
2. Evaluation of each solution and selection of the best ones.
3. Genetic manipulation to create new population.
4. Go back to step 2.

Figure 3 shows these stages. At the first stage, an initial population of potential solutions is created. Each element of the population is mapped onto a set of strings (the chromosome) to be manipulated by the genetic operators. In the second stage, the performance of each member of the population is assessed through an objective function imposed by the problem. This establishes the basis for selection of pairs of individuals that will be mated together during reproduction. For reproduction, each individual is assigned a fitness value derived from its raw performance measure, given by the objective function. This value is used in the selection to bias towards more fit individuals. Highly fit individuals, relative to the whole population, have a high probability of being selected for mating, whereas less fit individuals have a correspondingly low probability of being selected (Chipperfield and Fleming, 1994).

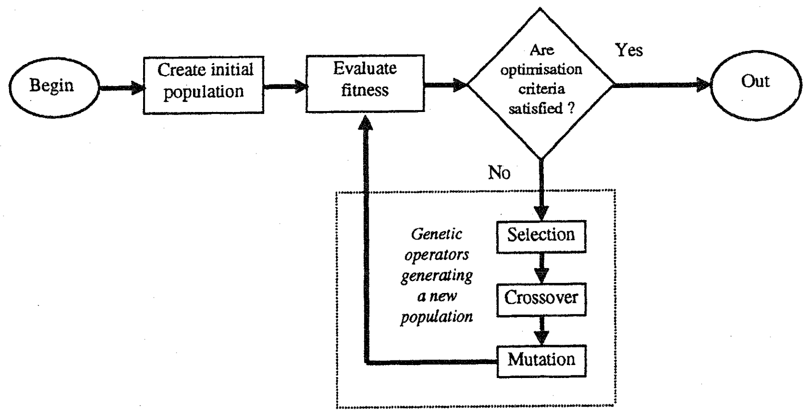


Figure 3. Genetic algorithm-simple working principles

In the manipulation phase, genetic operators such as crossover and mutation are used to produce a new population of individuals (offspring) by manipulating the "genetic information" usually called genes, possessed by the members (parents) of the current population. The crossover operator is used to exchange genetic information between pairs, on larger groups, of individuals. Mutation is generally considered to be a background operator which ensures that the search process is not trapped at local minimum, by introducing new genetic structures in the population.

After manipulation by the crossover and mutation operators, the individual strings are then, if necessary, decoded, the objective function evaluated, a fitness value assigned to each individual and individuals selected for mating according to their fitness, and so the process continues through subsequent generations. In this way, the average performance of individuals in a population is expected to increase, as good individuals are preserved and breed with one another and the less fit individuals die out. The GA is terminated when some criteria are satisfied, e.g., a certain number of generations completed or when a particular point in the search space is reached.

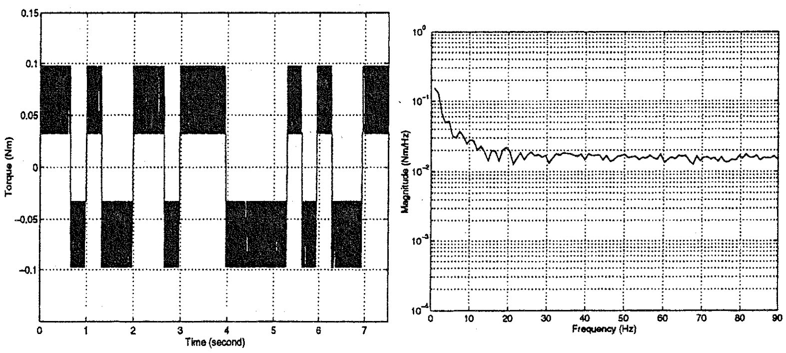
4. MODELLING WITH GENETIC ALGORITHMS

In this investigation, a GA is used for parametric identification of the flexible manipulator considered in this work, essentially to determine the vibration modes of the system. Randomly selected parameters are optimised for different, arbitrarily chosen order to fit to the system by applying the working mechanism of GA as described above. The fitness function utilised is the sum-squared error between the actual output, $y(n)$, of the system and the predicted output, $\hat{y}(n)$, produced from the input to the system and the optimised parameters;

$$f(e) = \sum_{i=1}^{n}(|y(n) - \hat{y}(n)|)^2 \qquad (2)$$

where n is the number of input/output samples. With the fitness function given above, the global search technique of the GA is utilised to obtain the best set of parameters among all the attempted orders for the system. The output of the system is thus simulated using the best sets of parameters.

The data set used for identification purposes was collected by exciting the manipulator by a composite signal constituting a combined bang-bang signal and pseudo random binary sequence (PRBS), referred to as composite PRBS signal. The frequency range of excitation was set to 0-100 Hz, which covers mainly the first three dominant modes of vibration of the system. The level of the bang-bang signal was chosen as ±0.065 Nm and of the PRBS as ±0.0325 Nm. The input signal thus used is shown in Figure 4.



(a) Time domain (b) Spectral density

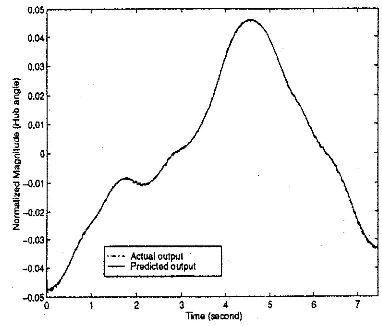
Figure 4. The composite PRBS torque input

The manipulator is modelled from the input torque to hub-angle, hub-velocity and end-point acceleration. These are referred to as the hub-angle model, hub-velocity model and end-point acceleration model respectively. In all the three cases it was attempted to implement the GA with different initial values and operator rates. Satisfactory results were achieved with the following set of parameters :

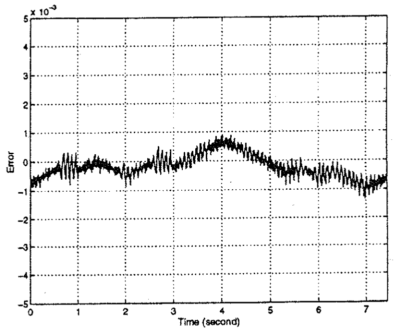
Generation gap	: 0.9
Crossover rate	: 0.7
Mutation rate (hub angle model)	: 0.00313
Mutation rate (hub velocity model)	: 0.00357
Mutation rate (end-point acceleration model)	: 0.00417

The corresponding results obtained with hub-angle, hub-velocity and end-point acceleration models are described below.

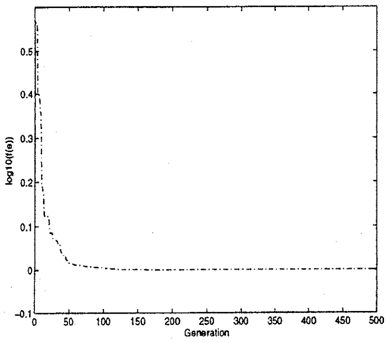
The hub-angle model was investigated with different model orders. The best result was achieved with an order 8. The GA was designed with 100 individuals in each generation. The maximum number of generations was set to 500. The algorithm achieved the best sum-squared error level of 0.000163 in the 500th generation. It was noted that a good level of accuracy was achieved with a smaller number of generations. Figure 5 shows the algorithm convergence and the simulated output with the parameter set that resulted in the 500th generation. The first three vibration modes, as found from the GA simulated output were at 11.112 Hz, 34.26 Hz and 63.89 Hz respectively.



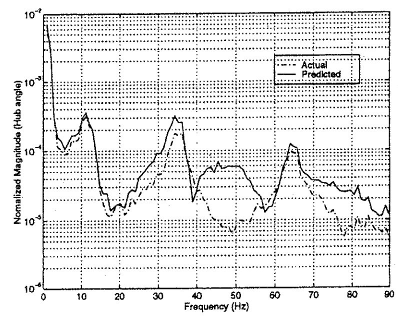
(a) Actual and predicted output



(b) Error between the actual and predicted output

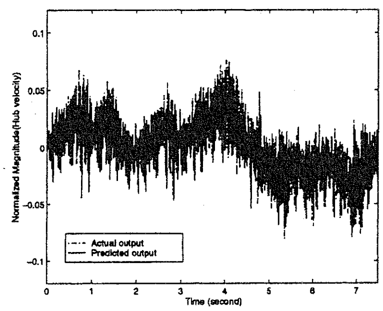


(c) Sum-squared error as function of number of training passes

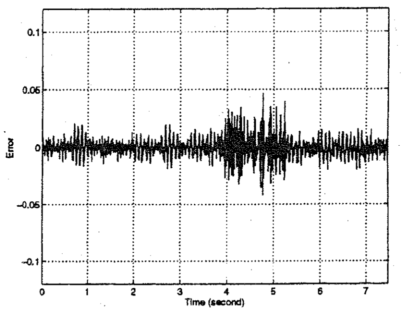


(d) Spectral density of the output

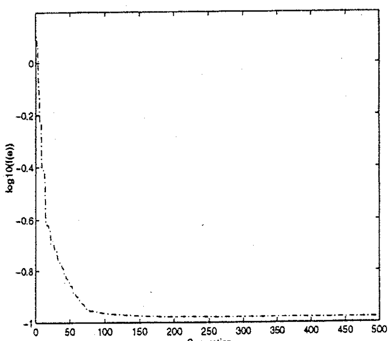
Figure 5. Hub-angle model with the GA



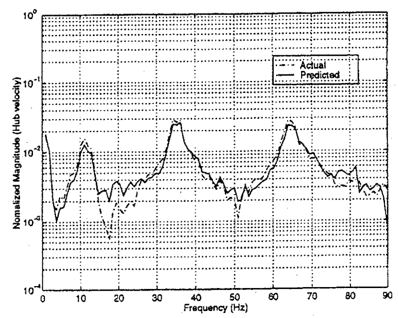
(a) Actual and predicted output



(b) Error between the actual and predicted output



(c) Sum-squared error as function of number of training passes

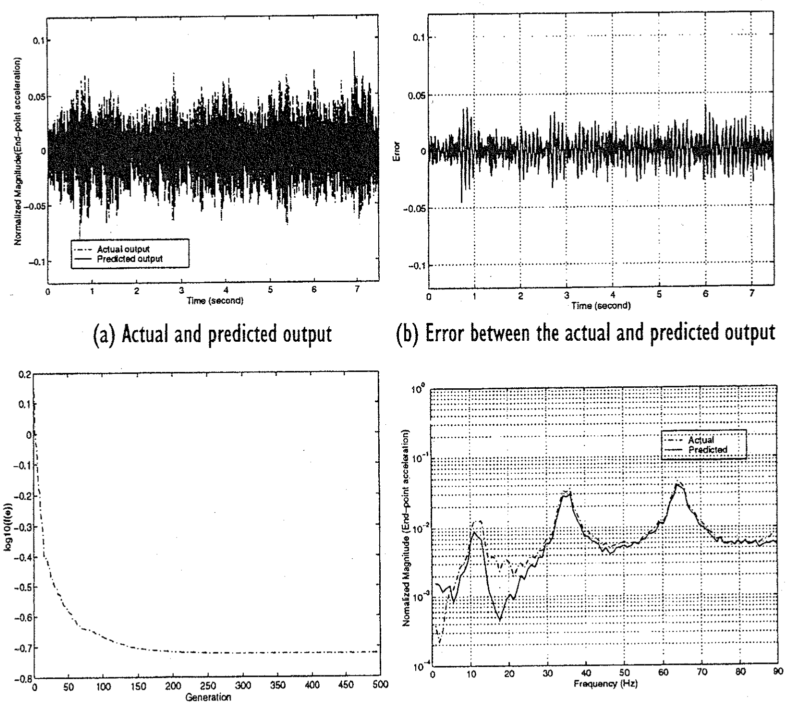


(d) Spectral density of the output

Figure 6. Hub-velocity model with the GA

The best result with hub-velocity model was achieved with an order 7. The number of individuals for each generation were selected as 100 and the maximum number of generations was set to 500. The algorithm achieved the best sum-squared error level of 0.10482 in the 500th generation. Figure 6 shows the algorithm convergence and the simulated output with the parameter set that resulted in the 500th generation. The first three resonance modes found from the GA simulated output were at 11.112 Hz, 34.26 Hz and 63.89 Hz respectively.

With the end-point acceleration model, the best result was achieved with an order 6. The number of individuals for each generation was selected as 100 and the maximum number of generations was set to 500. The algorithm achieved the best sum-squared error level of 0.18944 in the 500th generation. Figure 7 shows the algorithm convergence and the simulated output with the parameter set that resulted in the 500th generation. The first three vibration modes found from the GA simulated output were at 11.112 Hz, 34.26 Hz and 63.89 Hz.



(a) Actual and predicted output

(b) Error between the actual and predicted output

(c) Sum-squared error as function of number of training passes

(d) Spectral density of the output

Figure 7. End-point acceleration model with the GA

5. OPEN-LOOP CONTROL

Open loop control methods for vibration suppression in flexible manipulator systems consist of developing the control input through a consideration of the physical and vibration properties of the system. The method involves development of suitable forcing functions to reduce the system vibrations at the resonance modes. The methods commonly developed include shaped command methods, computed torque techniques and bang-bang control. The shaped command methods attempt to develop forcing functions that minimise the residual motion (vibration) and the effect of parameters that affect the resonance model (Aspinwall, 1980; Meckl and Seering, 1990; Singer and Seering, 1992; Tokhi and Azad, 1995; Poerwanto, 1998). Common problems of concern encountered in these methods include long move (response) time, instability due to un-reduced modes and controller robustness in case of large change of manipulator dynamics.

The aim of this investigation is to develop shaped command methods to reduce motion-induced vibrations in flexible manipulator systems during fast motion. The assumption is that the motion itself is the main source of system vibrations. Thus, torque profiles, which do not contain energy at the natural frequencies of the system, do not excite structural vibration. The procedure for determining shaped inputs that generate fast motions with minimum residual vibration has previously been addressed (Bayo, 1988; Meckl and Seering, 1988). The torque input needed to move a flexible manipulator from one point to another without vibration must have several properties: (a) it should have an acceleration and deceleration phase, (b) it should be able to be scaled for different step motions, and (c) it should have as sharp a cut-off frequency as required. These three properties of the required torque input will allow driving the manipulator system as quickly as possible without exciting its resonance modes. In this research, shaped torque inputs are developed on the basis of extracting the energies around the natural frequencies, and applied to the system in an open-loop configuration, so that the vibration in the flexible manipulator system during and after the movement is reduced. The approach adopted here for extraction of energy at the system resonance modes is based on filter theory. The filters are used for pre-processing the input to the plant, so that no energy is put into the system near its resonance frequencies. Investigations involving low-pass and band-stop filtered and Gaussian shaped torque inputs have previously been reported (Azad, 1994; Poerwanto, 1998), where the vibration modes have been determined by analysing the spectrum of the manipulator response. In the current work GAs are used to determine the vibration modes of the system.

5.1. Filtered torque input

The flexible manipulator system considered in this research is excited with a bang-bang input torque and the required system response is obtained as hub angle, hub velocity and end-point acceleration. However, with this excitation the system exhibits oscillatory motion. The strategy adopted here for reduction of system vibrations is to filter out any spectral energy near the natural frequencies of the system. Two approaches can be considered to filter out energy input at the natural frequencies. The first method is to pass the bang-bang signal through a low-pass filter. This will attenuate the energy at all frequencies above the filter cut-off frequency. The most important consideration is to achieve a steep roll-off rate at the cut-off frequency so that energy can pass at frequencies nearly up to the lowest natural frequency of the flexible manipulator. An alternative method to remove energy at system natural frequencies will be to use (narrow-band) band-stop filters with centre frequencies at selected (dominant) resonance modes of the system. Either Butterworth, Chebyshev or elliptic type filters can be employed for this purpose. In this work, the method is demonstrated using elliptic type filters.

The magnitude response with an elliptic filter is equiripple in both the passband and stopband. As a consequence of this a sharp transition from pass-band to stop-band for a given set of filter specifications is achieved by an elliptic filter design. Thus, the elliptic design is optimum in this sense. The squared magnitude response of a low-pass elliptic filter is of the form (Zverev, 1967)

$$|H(j\omega)|^2 = \frac{1}{1 + \eta^2 U_n^2\left[\frac{\omega}{\omega_c}\right]} \tag{3}$$

where, $U_n\{\omega\}$ is a Jacobian elliptic function of order n and n is a parameter related to the pass-band ripple. It is known that most efficient designs occur when the approximation error is equally spread over the pass-band and stop-band. Elliptic filters allow this objective to be achieved easily and thus, are most efficient from the viewpoint of yielding the smallest-order filter for a given set of specifications. Equivalently, for a given order and a given set of specifications, an elliptic filter has the smallest transition bandwidth. The filter order required for a pass-band ripple γ_1, stop-band ripple γ_2, and transition ratio $\frac{\omega_p}{\omega_s}$ is given as

$$n = \frac{K\left\{\frac{\omega_S}{\omega_C}\right\} K\left\{\left(1-\frac{\eta^2}{\gamma_1^2}\right)^{0.5}\right\}}{K\left\{\frac{\eta}{\gamma_1}\right\} K\left\{\left(1-\frac{\omega_P^2}{\omega_S^2}\right)^{0.5}\right\}} \tag{4}$$

where, $K\{\nu\}$ is the complete elliptic integral of the first kind, defined as

$$K\{\nu\} = \int_0^{\pi/2} (1 - \nu^2 sin^2\varphi)^{-0.5} d\varphi$$

$$\gamma_2 = (1 + \gamma_1^2)^{-0.5} \text{ and } \gamma_1 = 10log(1 + \eta^2)$$

The design relations for the low-pass filters given above can be utilised in normalised form to design the corresponding band-stop filters. This involves a transformation from low-pass to band-stop filter (Banks, 1990).

6. IMPLEMENTATIONS AND RESULTS

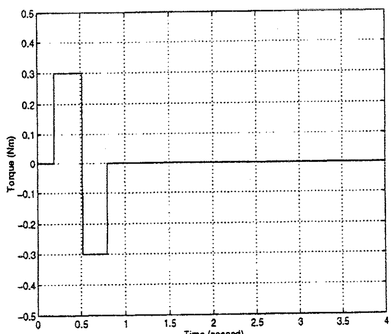
The first three modes of vibration of the system as determined, from modelling the manipulator with GAs, are given in Table II

Table II.
Modes determined from the GA-based model

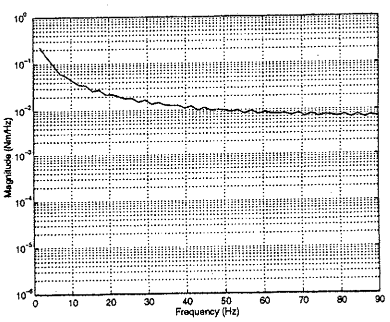
Model	Ist mode (Hz)	2nd mode (Hz)	3rd mode (Hz)
Hub-angle model	11.112	34.26	63.89
Hub-velocity model	11.112	36.11	63.89
End-point acceleration model	11.112	36.11	63.89

6.1. Response with bang-bang torque input

The flexible manipulator system considered in this research is excited with a bang-bang torque input and the corresponding system response is measured at the hub and end-point. Figure 8 shows the bang-bang torque input to the system. The magnitude of the torque ranges from .3 Nm to -0.3 Nm. It has an acceleration and a deceleration phase, so that when used as input the manipulator moves from its initial position and comes to rest at a target location. The hub-angle, hub-velocity, end-point acceleration and motor current, in response to the bang-bang torque input, are shown in Figures 9 – 12 respectively. It is noted that the response of the system is of oscillatory nature, dominantly characterised by the first few resonance modes. The first three resonance modes are considered in this work, as these dominantly characterise the flexible dynamics of the manipulator.

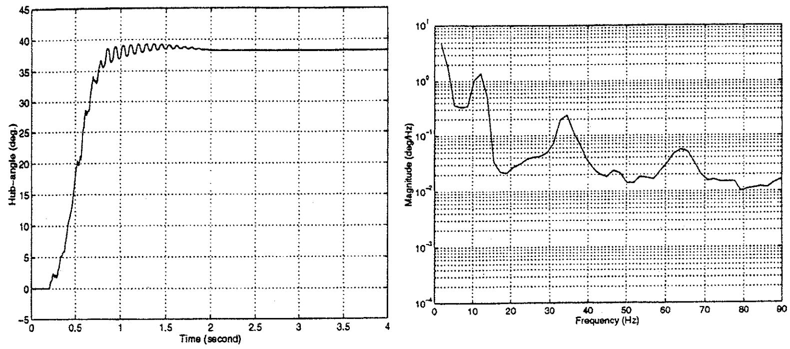


(a) Time domain



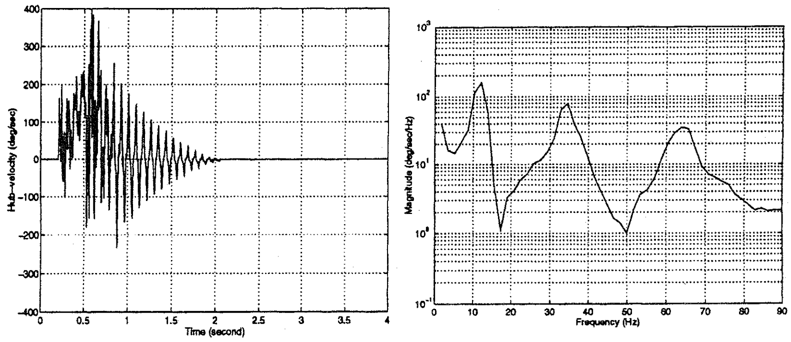
(b) Spectral density

Figure 8. The bang-bang torque input to the system



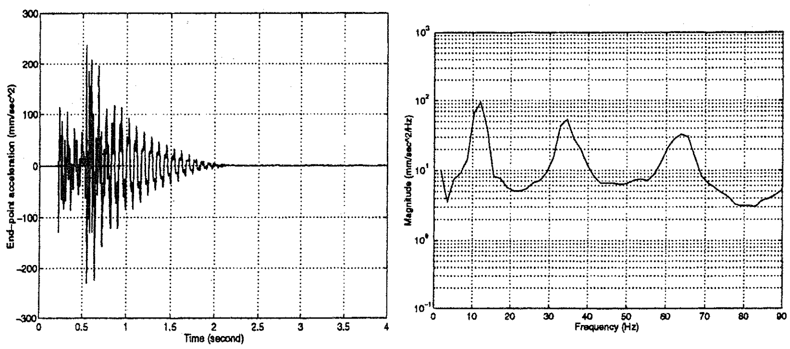
(a) Time domain (b) Spectral density

Figure 9. The hub-angle due to the bang-bang torque input



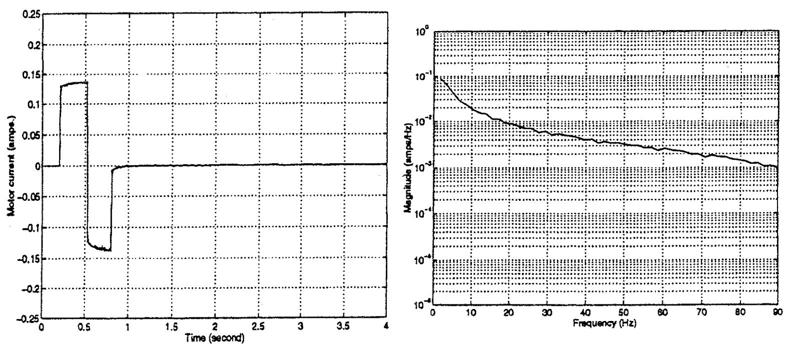
(a) Time domain (b) Spectral density

Figure 10. The hub-velocity due to the bang-bang torque input



(a) Time domain (b) Spectral density

Figure 11. The end-point acceleration due to the bang-bang torque input

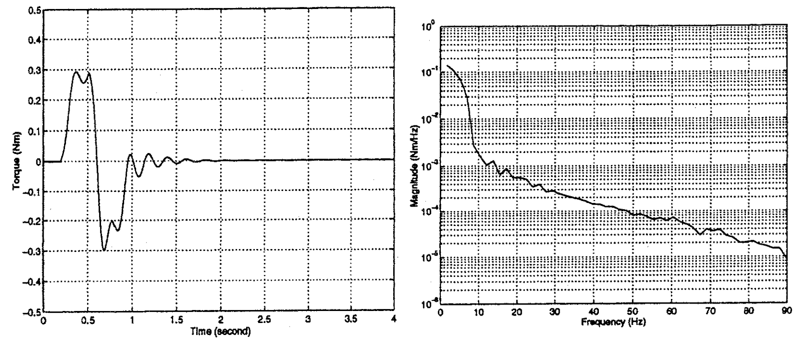


(a) Time domain (b) Spectral density

Figure 12. The motor current due to the bang-bang torque input

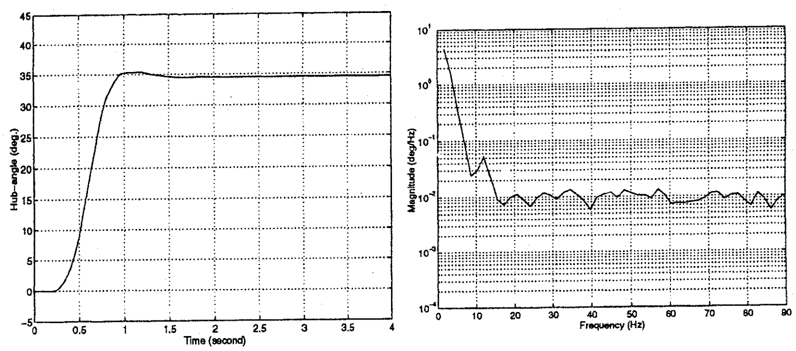
6.2. Response with low-pass filtered torque input

To investigate the performance of the system with low-pass filtered torque input a third-order low-pass elliptic filter with a cut-off frequency of 5.0 Hz was designed and used for pre-processing the bang-bang torque input. The significance of selecting the cut-off frequency at 5 Hz is that as it must be lower than the frequency of the first vibration mode of this system. The first vibration mode of the system is found to be at 11.112 Hz. To reduce the vibration of the system, the filtered bang-bang torque input is applied to the system and the response is measured at the hub and end-point.



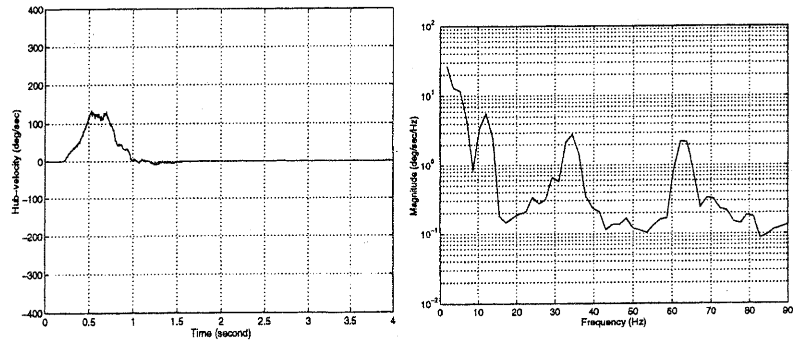
(a) Time domain (b) Spectral density

Figure 13. The elliptic low-pass filtered torque input



(a) Time domain (b) Spectral density

Figure 14. The hub-angle with the elliptic low-pass filtered torque input

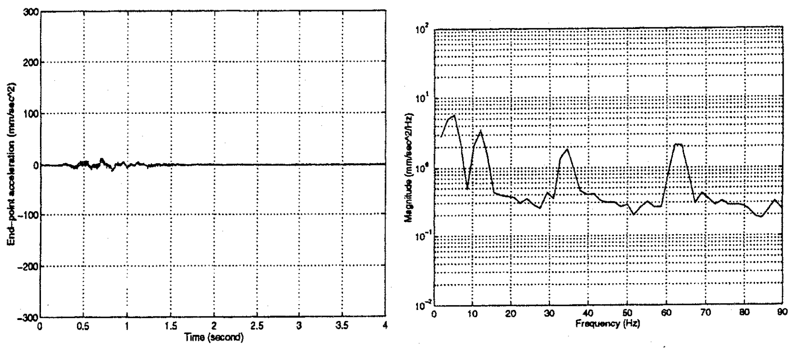


(a) Time domain (b) Spectral density

Figure 15. The hub-velocity with the elliptic low-pass filtered torque input

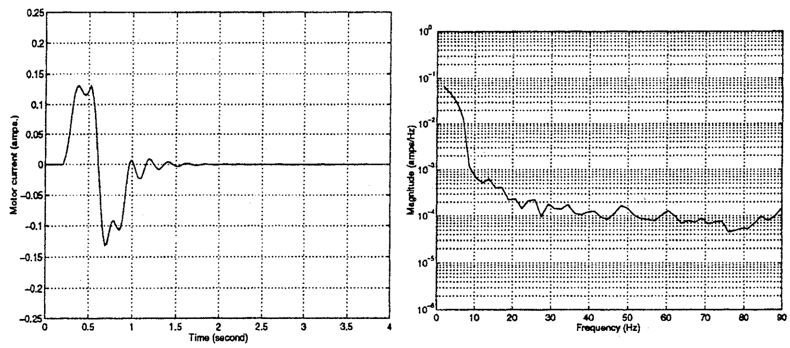
Figure 13 shows the low-pass elliptic filtered torque input. It is noted that the spectral energy input at the first three modes were reduced by 30.54 dB, 36.31 dB and 44.03 dB respectively as compared to the bang-bang torque input. The corresponding hub-angle, hub velocity, end-point acceleration and motor current are shown in Figures 14, 15, 16 and 17 respectively. It is noted that the response reached the desired steady-state level within a similar time-scale as with the bang-bang torque input.

However, the system vibrations were significantly reduced. The reduction in the level of oscillations in the hub displacement at the first, second and third modes were by 28.36 dB, 24.87 dB and 17.48 dB, respectively, in comparison to the bang-bang torque input. The reduction in the level of oscillations in the hub-velocity at the first, second and third modes were by 28.93 dB, 28.92 dB and 24.09 dB respectively. The corresponding reduction in the end-point acceleration was by 28.80 dB, 29.06 dB and 23.87 dB for the first, second and third vibration modes respectively. A similar level of reduction at the resonance modes of the system is evidenced in the motor current.



(a) Time domain (b) Spectral density

Figure 16. The end-point acceleration with the elliptic low-pass filtered torque input

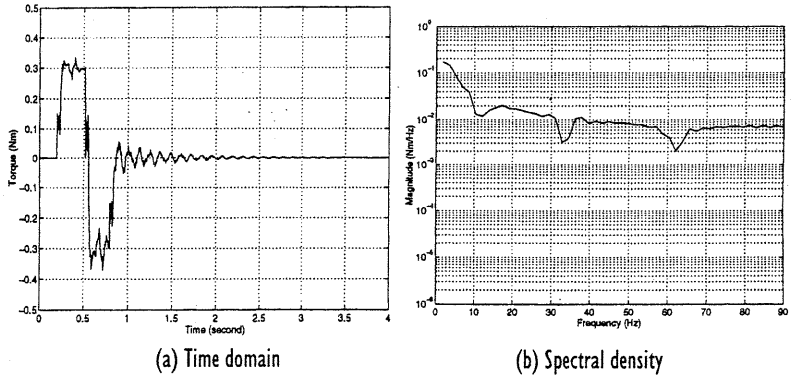


(a) Time domain (b) Spectral density

Figure 17. The motor current with the elliptic low-pass filtered torque input

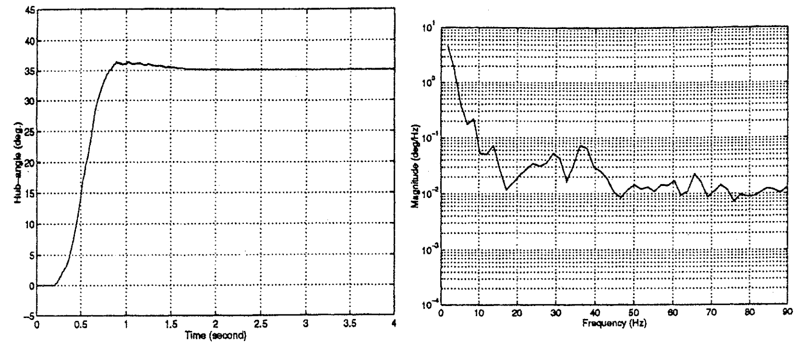
6.3. Response with band-stop filtered torque input

For effective suppression of vibration of the system the centre frequencies of the band-stop filters have to be designed at locations as close as possible to the system's natural frequencies (vibration modes). The centre frequencies of the band-stop filters for the first, second and third resonance modes of the system were chosen in the light of the results presented in Section 4, as 11.112 Hz, 36.11 Hz and 63.89 Hz respectively.



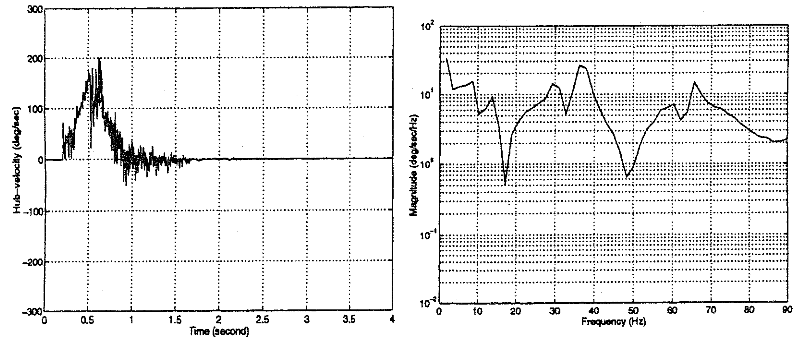
(a) Time domain (b) Spectral density

Figure 18. The elliptic band-stop filtered torque input



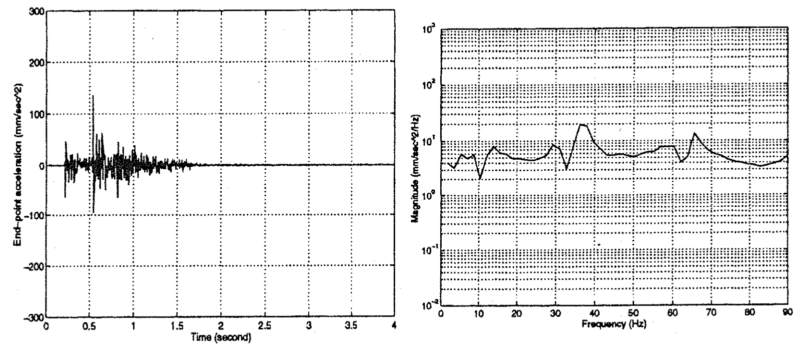
(a) Time domain (b) Spectral density

Figure 19. The hub-angle with the elliptic band-stop filtered torque input



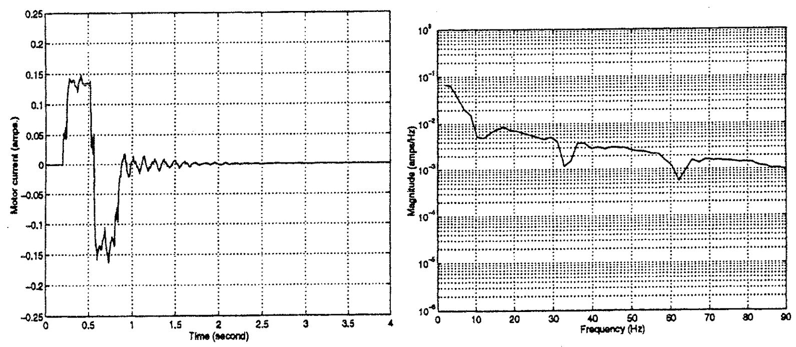
(a) Time domain (b) Spectral density

Figure 20. The hub-velocity with the elliptic band-stop filtered torque input



(a) Time domain (b) Spectral density

Figure 21. The end-point acceleration with the elliptic band-stop filtered torque input



(a) Time domain (b) Spectral density

Figure 22. The motor current with the elliptic band-stop filtered torque input

Three third order elliptic band-stop filters were designed in cascade, each with a bandwidth of 5.0 Hz, and centre frequencies at 11.112 Hz, 36.11 Hz and 63.89 Hz for the first, second and third modes respectively. The filters were used to process the bang-bang torque input and the resulting torque was used to excite the system and the corresponding system response was recorded. Figure 18 shows the elliptic band-stop filtered torque input. It is noted that the spectral attenuation in the input in comparison to the bang-bang torque input is 9.394 dB, 10.51 dB and 7.778 dB for the first, second and third modes respectively. The corresponding hub-displacement is shown in Figure 19. The spectral attenuation achieved at the first three resonance modes was 28.84 dB, 17.43 dB and 14.06 dB for the first second and third vibration modes respectively. The corresponding hub-velocity is shown in Figure 20. The spectral attenuation achieved at the first three resonance modes in the case of hub-velocity was 27.99 dB, 17.23 dB and 15.95 dB for the first, second and third vibration modes respectively. The corresponding end-point acceleration and motor current are shown in Figures 21 and 22 respectively. The corresponding end-point acceleration and motor current are shown in Figures 21 and 22 respectively. The spectral attenuation achieved at the first three resonance modes in the case of end-point acceleration was 24.75 dB, 16.80 dB and 16.08 dB and in case of the motor current was 9.71 dB, 10.24 dB and 7.760 dB for the first, second and third modes respectively.

7. COMPARATIVE ASSESSMENT

A comparative performance of the system with the low-pass and band-stop filtered torque inputs is presented in Table III. It is evident from the results that both types of filter have performed well in reducing the system vibrations. It is also noted that better performance has been achieved with low-pass filtered torque input as compared to band-stop filtered torque input. This is due to the indiscriminate spectral attenuation in the low-pass filtered torque input at all the resonance modes of the system.

Table III.

Comparative performance of elliptic low-pass (E-LP) and elliptic band-stop (E-BS) filters in suppressing system vibrations

Response	Torque Input	First mode		Second mode		Third mode	
		Magnitude	Reduction (dB)	Magnitude	Reduction (dB)	Magnitude	Reduction (dB)
Input torque	Bang-bang	0.03536	-	0.01301	-	0.00816	-
	E-LP filtered	0.00105	30.54	0.00020	36.31	0.00005	44.03
	E-BS filtered	0.01199	9.394	0.00388	10.51	0.00333	7.785
Hub angle	Bang-bang	1.391145	-	0.236565	-	0.056026	-
	E-LP filtered	0.053160	28.36	0.013504	24.87	0.007491	17.48
	E-BS filtered	0.050295	28.84	0.031808	17.43	0.011108	14.06
Hub velocity	Bang-bang	159.1317	-	79.41811	-	35.03611	-
	E-LP filtered	5.692472	28.93	2.844419	28.92	2.188725	24.09
	E-BS filtered	6.34109	27.99	10.91735	17.23	5.58608	15.95
End point Acceleration	Bang-bang	95.27815	-	53.88137	-	32.77781	-
	E-LP filtered	3.41779	28.80	1.899551	29.06	2.098449	23.87
	E-BS filtered	5.51402	24.75	7.785512	16.80	5.145747	16.08
Motor Current	Bang-bang	0.015244	-	0.005017	-	0.002314	-
	E-LP filtered	0.000598	29.35	0.000178	29.02	0.000069	30.53
	BS-E filtered	0.004981	9.71	0.001542	10.24	0.000947	7.760

8. CONCLUSION

Low-pass and band-stop filtered torque inputs have been developed and investigated in an open-loop control configuration for control of a single-link flexible manipulator. Significant improvement in the reduction of system vibrations has been achieved with these control functions as compared to a bang-bang torque input. It is noted that system vibrations are significantly reduced with both types of filter. It has been shown that better performance is achieved with low-pass filtered torque input as compared to band-stop filtered torque input. However, it is possible to pass more information to the system with a band-stop filtering approach. Moreover, utilisation of band-stop filtered torque input is advantageous in that spectral attenuation in the input at selected resonance modes of the system can be achieved. Thus, the open-loop control strategy based on band-stop filters can be considered optimal in this sense.

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