Hybrid learning control schemes with input shaping of a flexible manipulator system

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Abstract

The paper describes a practical approach to investigate and develop a hybrid iterative learning control scheme with input shaping. An experimental flexible manipulator rig and corresponding simulation environment are used to demonstrate the effectiveness of the proposed control strategy. A collocated proportional-derivative (PD) controller utilizing hub-angle and hub-velocity feedback is developed for control of rigid-body motion of the system. This is then extended to incorporate iterative learning control with acceleration feedback and genetic algorithms (GAs) for optimization of the learning parameters and a feedforward controller based on input shaping techniques for control of vibration (flexible motion) of the system. The system performance with the controllers is presented and analysed in the time and frequency domains. The performance of the hybrid learning control scheme with input shaping is assessed in terms of input tracking and level of vibration reduction. The effectiveness of the control schemes in handling various payloads is also studied.
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1. Introduction

Flexible manipulators exhibit many advantages over their rigid counterparts: they require less material, are lighter in weight, have higher manipulation speed, lower power consumption, require smaller actuators, are more maneuverable and transportable, are safer to operate due to reduced inertia, have enhanced back-drive ability due to elimination of gearing, have less overall cost and higher payload to robot weight ratio [1]. However, the control of flexible manipulators to maintain accurate positioning is an extremely challenging problem. Due to the flexible nature and distributed characteristics of the system, the dynamics are highly non-linear and complex. Problems arise due to precise positioning requirement, vibration due to system flexibility, difficulty in obtaining accurate model of the sys-

tem and non-minimum phase characteristics [2,3]. In this respect, a control mechanism that accounts for both the rigid body and flexural motions of the system is required. If the advantages associated with lightness are not to be sacrificed, accurate models and efficient control strategies for flexible robot manipulators have to be developed.

The control strategies for flexible robot manipulator systems can be classified as feed-forward (open-loop) and feedback (closed-loop) [4]. Feed-forward techniques for vibration suppression involve developing the control input through consideration of the physical and vibrational properties of the system, so that system vibrations at response modes are reduced. This method does not require any additional sensors or actuators and does not account for changes in the system once the input is developed. On the other hand, feedback-control techniques use measurement and estimations of the system states to reduce vibration. Feedback controllers can be designed to be robust to parameter uncertainty. For flexible manipulators, feedforward and feedback control techniques are used for

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vibration suppression and position control, respectively. An acceptable system performance without vibration that accounts for system changes can be achieved by developing a hybrid controller consisting of both control techniques [4]. Thus, a properly designed feedforward controller is required, with which the complexity of the required feedback controller can be reduced.

Many industrial applications of robot manipulators involve iterative repeated cycles of events. Thus, it is important to minimize errors in trajectory tracking of such manipulators, and this can be achieved with suitable learning strategies. The basic idea behind iterative learning control (ILC) is that the controller should learn from previous cycles and perform better every cycle. Such ideas were first presented by Arimoto et al. [5] in 1984 who proposed a learning control scheme called the improvement process, and since then several researchers have addressed robot control in combination with iterative learning control [6–8]. The convergence properties when using iterative learning control form another very important aspect, addressed already in [5], and further covered in many articles [9,10]. In this paper ILC is studied as a complement to conventional feedforward and feedback control and the effectiveness of the resulting scheme is assessed in input tracking and vibration reduction of a flexible robot manipulator.

The paper presents investigations into the development of hybrid learning control with input shaping for input tracking and end-point vibration suppression of a flexible manipulator system. A constrained planar single-link flexible manipulator is considered and an experimental setup incorporating the real-time workshop toolbox of MALTAB is used for evaluation of performance of the control strategies. A finite element (FE) simulation algorithm characterizing the flexible manipulator is also utilized in theoretical assessment of the control methods. To demonstrate the effectiveness of the proposed control schemes, initially a joint-based collocated PD control utilising hub-angle and hub-velocity feedback is developed for control of rigid body motion of the manipulator. This is then extended to incorporate an ILC scheme, with acceleration feedback using genetic algorithms (GAs) for optimization of the learning parameters and input shaping for vibration suppression of the manipulator. For non-collocated control, end-point displacement feedback through a PID control configuration is developed whereas in the feedforward scheme, an input shaping technique is utilised as this has been shown to be effective in reducing system vibration [11]. Experimental results of the response of the manipulator with the controllers are presented in time and frequency domains. The performances of the hybrid learning control with input shaping are assessed in terms of input tracking and level of vibration reduction in experimental and simulation environments. The effectiveness of the controllers is also studied with different loading conditions. Finally, a comparative assessment of the hybrid learning control scheme in input tracking and vibration suppression of the manipulator is presented.

2. The flexible manipulator system

Fig. 1 shows the laboratory-scale single-link experimental rig used in this work. This consists of three main components: a flexible arm and the driving motor, measuring devices and a digital processor. The flexible arm is constructed using a piece of thin aluminium alloy with length $L = 0.9$ m, width $= 19.008$ mm, thickness $= 3.2004$ mm, Young's modulus $E = 71 \times 10^9$ N/m^2, area moment of inertia $I = 5.1924$ m^4, mass density per unit volume $\rho = 2710$ kg/m^3 and hub inertia $I_h = 5.8598 \times 10^{-4}$ kg m^2. The manipulator can be considered as a pinned-free flexible arm, which can bend freely in the horizontal plane but is relatively stiff in vertical bending and torsion. The rig is equipped with a U9M4AT type printed circuit armature motor at the hub, driving the flexible manipulator. The motor is chosen as the drive actuator due to its low inertia and inductance and physical structure. Moreover, the printed armature gives a smooth torque output even at low speeds and the absence of magnetic material in the armature gives a linear torque to current relationship [12]. A linear drive amplifier LA5600 manufactured by Electro-Craft Corporation is used as a motor driver [13]. This is a bi-directional drive amplifier, as the motor needs to be driven in both directions to control the manipulator vibration.
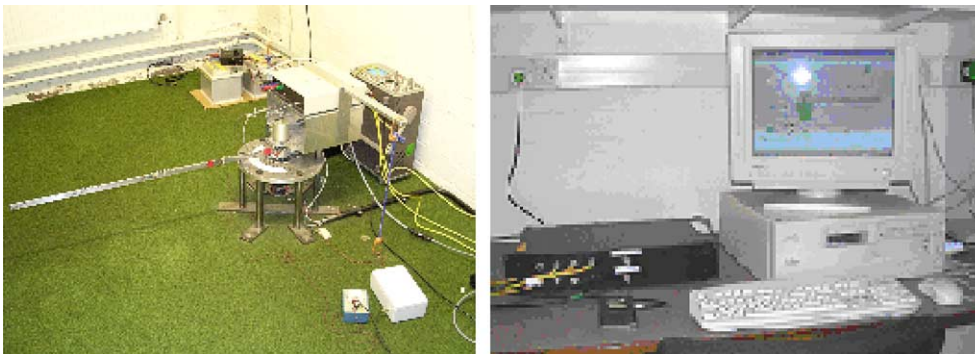

Fig. 1. The laboratory-scale single-link flexible manipulator.

The digital processor used is an IBM compatible PC based on an Intel(r) celeron™ processor. Data acquisition and control are accomplished through the utilization of PCL-812PG board. This board can provide a direct interface between the processor, actuator and sensors. The experimental setup requires one analogue output to the motor driver amplifier and four analogue inputs from the hub-angle, hub-velocity, end-point acceleration and motor current sensor. The interface board is used with a conversion speed of 25 µs for A/D conversion and a settling time of 20 µs for D/A conversion, which are adequate for the system under consideration.

A simulation algorithm characterising the dynamic behaviour of the manipulator has previously been developed using the finite element (FE) method [4]. This is used in this work as a platform for theoretical test and evaluation of the proposed control approaches.

3. Control schemes

In this section, control schemes for rigid-body motion control and vibration suppression of the flexible manipulator are proposed. Initially, a collocated PD control is designed. This is then extended to incorporate an ILC scheme for control of vibration of the system.

3.1. Collocated PD control

A common strategy in the control of manipulator systems involves the utilization of PD feedback of collocated sensor signals. Such a strategy is adopted at this stage of the investigation here. A block diagram of the PD controller is shown in Fig. 2, where K_p and K_v are the proportional and derivative gains, respectively, θ and $\dot{\theta}$ represent hub angle and hub velocity, respectively, R_f is the reference hub angle and A_c is the gain of the motor amplifier. Here the motor/amplifier set is considered as a linear gain A_c. To design the PD controller a linear state-space model of the flexible manipulator was obtained by linearising the equations of motion of the system. The control signal $u(s)$ in Fig. 2 can be written as

$$u(s) = A_c[K_p\{R_f(s) - \theta(s)\} - K_v s\theta(s)] \tag{1}$$

where s is the Laplace variable. The closed-loop transfer function is, therefore, obtained as

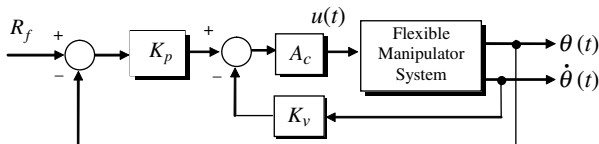$$\frac{\theta(s)}{R_f(s)} = \frac{K_p H(s) A_c}{1 + A_c K_v(s + K_p/K_v)H(s)} \tag{2}$$

where $H(s)$ is the open-loop transfer function from the input torque to hub angle, given by

$$H(s) = \mathbf{C}(s\mathbf{I} - \mathbf{A})^{-1}\mathbf{B} \tag{3}$$

where $\mathbf{A}$, $\mathbf{B}$ and $\mathbf{C}$ are the characteristic matrix, input matrix and output matrix of the system, respectively, and $\mathbf{I}$ is the identity matrix. The closed-loop poles of the system are, thus, given by the closed-loop characteristic equation as

$$1 + K_v(s + Z)H(s)A_c = 0 \tag{4}$$

where $Z = K_p/K_v$ represents the compensator zero which determines the control performance and characterises the shape of root locus of the closed-loop system. In this study, the root locus approach is utilized to design the PD controller. Analyses of the root locus plot of the system show that dominant poles with maximum negative real parts could be achieved with $Z \approx 2$ and by setting K_p between 0 and 1.2 [14].

3.2. Hybrid collocated PD with iterative learning control

A hybrid collocated PD control structure for control of rigid-body motion of the flexible manipulator with ILC is proposed in this section. In this study, an ILC scheme is developed using PD-type learning algorithm.

Iterative learning control has been an active research area for more than a decade, mainly inspired by the pioneering work of Arimoto et al. [5]. Learning control begun with the fundamental principle that repeated practice is a common mode of human learning. Given a goal (regulation, tracking, or optimization), learning control, or more specifically, iterative learning control refers to the mechanism by which necessary control can be synthesized by repeated trials. Moore [15] describes ILC as an approach to improving the transient response performance of a system that operates repetitively over a fixed interval. This is especially applicable to a system such as industrial robot which accomplishes most of its tasks repetitively over a period of time. Consider a robot arm in which a number of conditions such as varying the input parameters and disturbances are imposed. Performance of the arm, e.g. trajectory control can be evaluated, changed or improved iteratively by means of using the previous response. This is in turn incorporated in the control strategy during the next cycle to improve its performance. In this way, an ILC scheme is established in which unlike conventional adaptive control approaches, the control strategy is changed by changing the command reference signal and not the controller itself. Arimoto and his co-workers later developed the idea further [5].

Fig. 3 illustrates the basic idea of ILC. The input signal $\Psi_k(t)$ and output signal $x_k(t)$, are stored in the memory (some type of memory device is implicitly assumed in the block labeled "learning controller"). By using the desired output of the system $x_d(t)$ and the actual output $x_k(t)$, the performance error at kth trial can be defined as

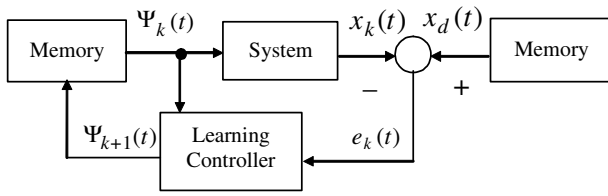Fig. 2. The collocated PD control structure.

Fig. 3. Iterative learning control configuration.

$$e_k(t) = x_d(t) - x_k(t) \tag{5}$$

The aim of ILC is to iteratively compute a new compensation input signal $\Psi_{k+1}(t)$, which is stored for use in the next trial. The next input command is chosen in such a way to guarantee that the performance error will be reduced in the next trial. The important task in the design of a learning controller is to find an algorithm for generating the next input in such a way that the performance error is reduced on successive trials. In other words, the algorithm needs to lead to the convergence of the error to minimum. Another consideration is that it is desirable to have the convergence of the error without or at least with minimal knowledge of the model of the system. Further, the algorithm should be independent of the functional form of the desired response, $x_d(t)$. Thus, the learning controller would "learn" the best possible control signal for a particular desired output trajectory even if it is newly introduced without the need to reconfigure the algorithm.

In this work a learning algorithm of the following form is considered:

$$\Psi_{k+1} = \Psi_k + \Phi e_k + \Gamma \dot{e}_k \tag{6}$$

where Ψ_{k+1} is the next control signal, Ψ_k is the current control signal, $e_k = (x_d - x_k)$ is the current error input. Φ, Γ are suitable positive definite constants (or learning parameters).

A block diagram of the scheme is shown in Fig. 4. It is obvious that the algorithm contains a constant and derivative coefficient of the error. In other words, the expression can be simply called proportional-derivative or PD-type learning algorithm. A slightly modified learning algorithm to suit the application is employed here. Instead of using the absolute position tracking error e_k, a sum-squared tracking error e_k is used. Fig. 4 shows a block diagram describing the above expression. This is used with PD col-
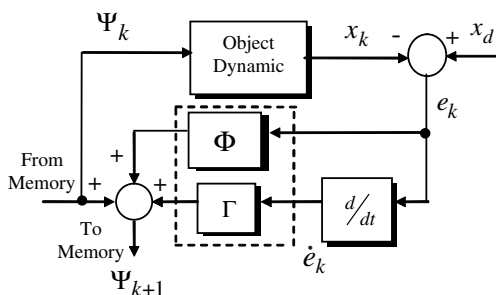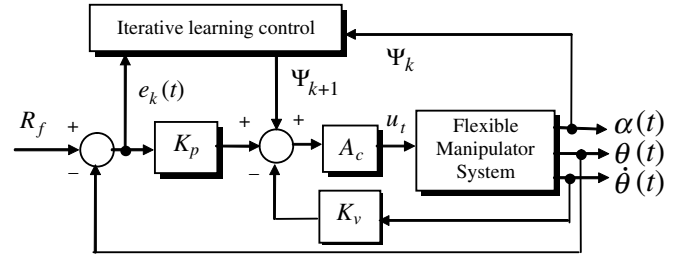

Fig. 4. PD-type learning algorithm.

Fig. 5. The collocated PD with iterative learning control structure.

located control, to realise the hybrid collocated PD with ILC. This is shown in Fig. 5.

3.3. GA based hybrid learning control

Fig. 4 shows the PD-type learning control scheme. The performance of the PD-type learning control depends upon the proportional gain Φ and derivative gain Γ. Stability, settling time, maximum overshoot and many other system performance indicators depend upon the values of Φ and Γ. The proposed strategy utilizes GA as an optimization and search tool to determine optimum values for the gains. The performance index or the cost function chosen is the error taken by the system to reach and stay within a range specified by absolute percentage of the final value. Hence, the role of GA is to find optimum values of the gains Φ and Γ. In this case, integral of absolute error (IAE) is used for minimizing the error and generating the controller parameters:

$$\text{IAE} = \int_0^T \left| \frac{\sum \text{Error}^2}{N} \right| dt \tag{7}$$

where $\text{Error} = r(t) - y(t)$, $N = $ size of sample, $r(t) = $ reference input and $y(t) = $ measured variable. Thus, the function in Eq. (7) can be minimized by applying a suitable tuning algorithm. Genetic algorithm is used here as a tuning algorithm. Genetic algorithms constitute stochastic search methods that have been used as optimization tools in a wide spectrum of applications such as parameter identification and control structure design [16,17]. GAs have also found widespread use in controller optimization particularly in the fields of fuzzy logic [18] and neural networks [19]. The GA used here initializes a random set of population of the two variables Φ and Γ. The algorithm evaluates all members of the population based on the specified performance index. The algorithm then applies the GA operators such as reproduction, crossover and mutation to generate a new set of population based on the performance of the members of the population. The best member or gene of the population is chosen and saved for next generation. It again applies all operations and selects the best gene among the new population. The best gene of the new population is compared to best gene of previous population and the best among all will be selected to represent Φ and Γ. If a predefined termination criterion is not met, a new population is obtained in the same way as above. The

termination criterion may be formulated as the magnitude of difference between index value of previous generation and present generation becoming less than a pre-specified value. The process continues till the termination criterion is fulfilled. To assess the potential of the learning algorithm further it is augmented with command shapers next and its performance assessed within the flexible manipulator.

3.4. Hybrid control with input shaping

The most widely used and cited command shaping scheme is probably the one developed by Singer and co-workers [20]. The method has been shown to be effective in the control of vibration of flexible manipulators [11,21]. Previous investigations have considered a combined feedforward control incorporating input shaping and feedback control incorporating PD control for a single-link flexible manipulator [22]. The current work proposes a control structure combining input shaping in the forward path with iterative learning and PD control in a feedback configuration.

The method of input shaping involves convolving a desired command with a sequence of impulses. The design objectives are to determine the amplitude and time location of the impulses. A brief derivation is given below. Further details can be found in [11]. The corresponding design relations for achieving zero residual single mode vibration, ensuring that the shaped command input produces the same rigid body motion as the unshaped command, yields a two-impulse sequence with parameters as

$$t_1 = 0, \quad t_2 = \frac{\pi}{\omega_d}$$
$$A_1 = \frac{1}{1+H}, \quad A_2 = \frac{H}{1+H} \tag{8}$$

where ω_n and ζ represent the natural frequency and damping ratio, respectively, $H = e^{-\frac{\zeta\pi}{\sqrt{1-\zeta^2}}}$, $\omega_d = \omega_n\sqrt{1-\zeta^2}$, t_j and A_j are the time location and amplitude of impulse j, respectively. The robustness of the input shaper to errors in natural frequencies of the system can be increased by solving the derivatives of the system vibration. This yields a four-impulse sequence with parameters as

$$t_1 = 0, \quad t_2 = \frac{\pi}{\omega_d}, \quad t_3 = \frac{2\pi}{\omega_d}, \quad t_4 = \frac{3\pi}{\omega_d}$$
$$A_1 = \frac{1}{1+3H+3H^2+H^3}, \quad A_2 = \frac{3H}{1+3H+3H^2+H^3}$$
$$A_3 = \frac{3H^2}{1+3H+3H^2+H^3}, \quad A_4 = \frac{H^3}{1+3H+3H^2+H^3} \tag{9}$$

where H is as in Eq. (8).

To handle higher vibration modes, an impulse sequence for each vibration mode can be designed independently. Then the impulse sequences can be convoluted together to form a sequence of impulses that attenuates vibration at higher modes. For any vibratory system, the vibration
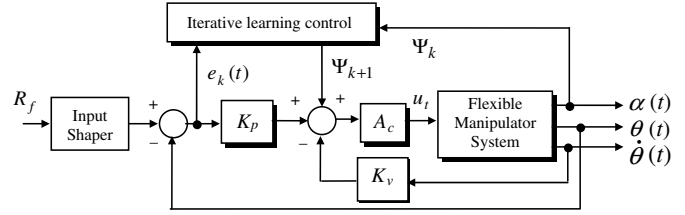

Fig. 6. The PDILC control with input shaping structure.

reduction can be accomplished by convolving any desired system input with the impulse sequence. This yields a shaped input that drives the system to a desired location without vibration. Incorporating the input shaping into PD-ILC structure results in the combined PD-ILC and input shaping control structure shown in Fig. 6.

4. Results and discussion

In this section, the proposed control schemes are implemented and tested within the simulation and experimental environments of the flexible manipulator and the corresponding results are presented. The manipulator is required to follow a trajectory at $\pm 75°$ as shown in Fig. 7. System responses, namely hub-angle and end-point acceleration are observed. To assess the vibration reduction in the system in the frequency domain, power spectral density (SD) of response at the end-point is obtained. Thus, the first three modes of vibration of the system are considered as these dominantly characterise the behaviour of the manipulator. Figs. 8 and 9 show simulated and experimental responses of the manipulator at the end-point. Comparisons of the responses of the manipulator without payload show that a close agreement between experimental and simulation results at the resonance frequencies was achieved. It is noted in the simulation results that the first three modes of vibration of the system converged to 13.47 Hz, 35.43 Hz and 65.37 Hz, respectively. The experimental results, however, gave 12.46 Hz, 36 Hz and 65.1 Hz
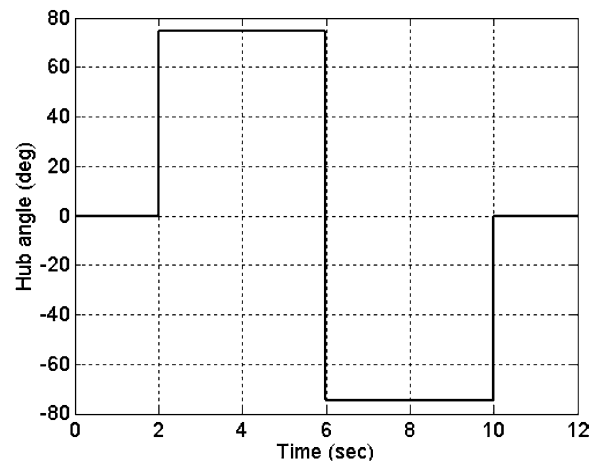

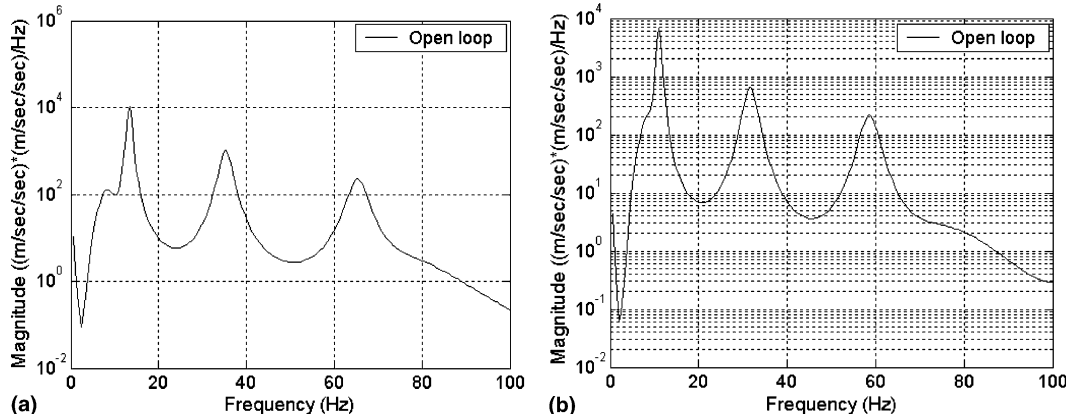Fig. 7. The reference hub angle.

Fig. 8. Simulated open loop end-point acceleration: (a) spectral density without payload; (b) spectral density with 30 g payload.
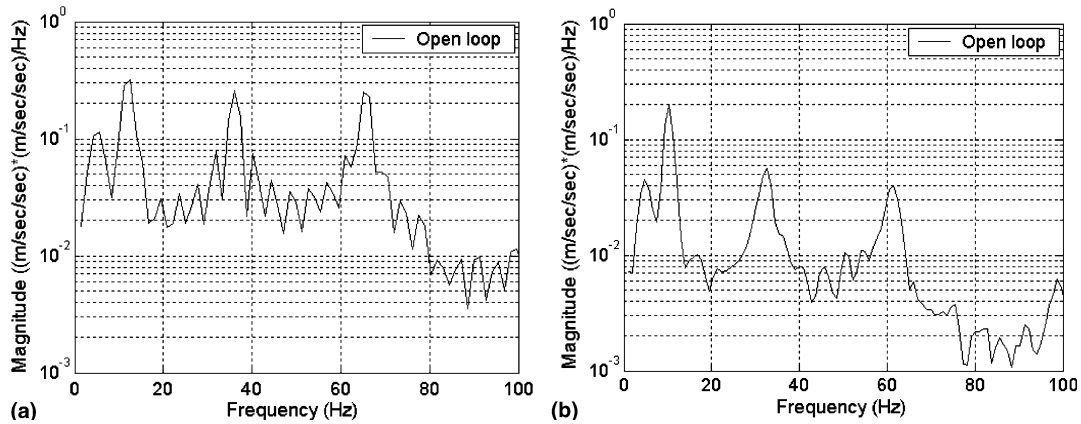

Fig. 9. Experimental open loop end-point acceleration: (a) spectral density without payload; (b) spectral density with 30 g payload.

for the first, second and third modes, respectively. The corresponding errors between the simulation and experimental results at modes 1, 2 and 3 are accordingly 8.1%, 1.6% and 0.4%, which are considered negligibly small. For the manipulator with 30 g payload, on the other hand, the vibration frequencies were obtained as 10.98 Hz, 31.43 Hz, 58.38 Hz for the simulated system and 10.24 Hz, 32.58 Hz, 61.45 Hz for the experimental system. The corresponding errors between the simulation and experimental results at modes 1, 2 and 3 with 30 g payload are thus 7.2%, 3.5% and 5%, respectively, which are considered negligibly small. These results were considered as the system response in open-loop and subsequently used to evaluate the control techniques.

The collocated PD control scheme was designed based on root locus analysis, from which K_p, K_v and A_c were deduced as 0.64, 0.32 and 0.01 for the simulated system setup and 2.4, 1.2 and 1 for the experimental setup, respectively. The corresponding system response without and with payload is shown in Figs. 10 and 11. The closed-loop parameters with the PD control will subsequently be used to design and evaluate the performance of iterative learning acceleration feedback control schemes in terms of input tracking capability and level of vibration reduction. The

results in Fig. 10 for the collocated PD control will be used for comparative assessment of the hybrid control schemes proposed in Section 3.

The (PD-ILC) scheme, was designed on the basis of the dynamic behaviour of the closed-loop system. The parameters of the learning algorithm, Φ and Γ were tuned using GA over the simulation environment and experimental setup. The parameters used for simulated and experimental systems were as follows:

Simulation	Experimental
Without payload:	Without payload:
$\Phi = 0.0015$, $\Gamma = 0.0011$	$\Phi = 0.0015$, $\Gamma = 0.0011$
With 30 g payload:	With 30 g payload:
$\Phi = 0.0007$, $\Gamma = 0.00059$	$\Phi = 0.0012$, $\Gamma = 0.0007$

The GA was designed with 80 individuals in each generation for without payload and 60 individuals in each generation for with 30 g payload. The maximum number of generations was set to 100 for without payload and 80 for with 30 g payload. The algorithm achieved a minimum IAE level in the 70th generation for without and with payload. Figs. 12, 13 and Table 1 show the algorithm conver-
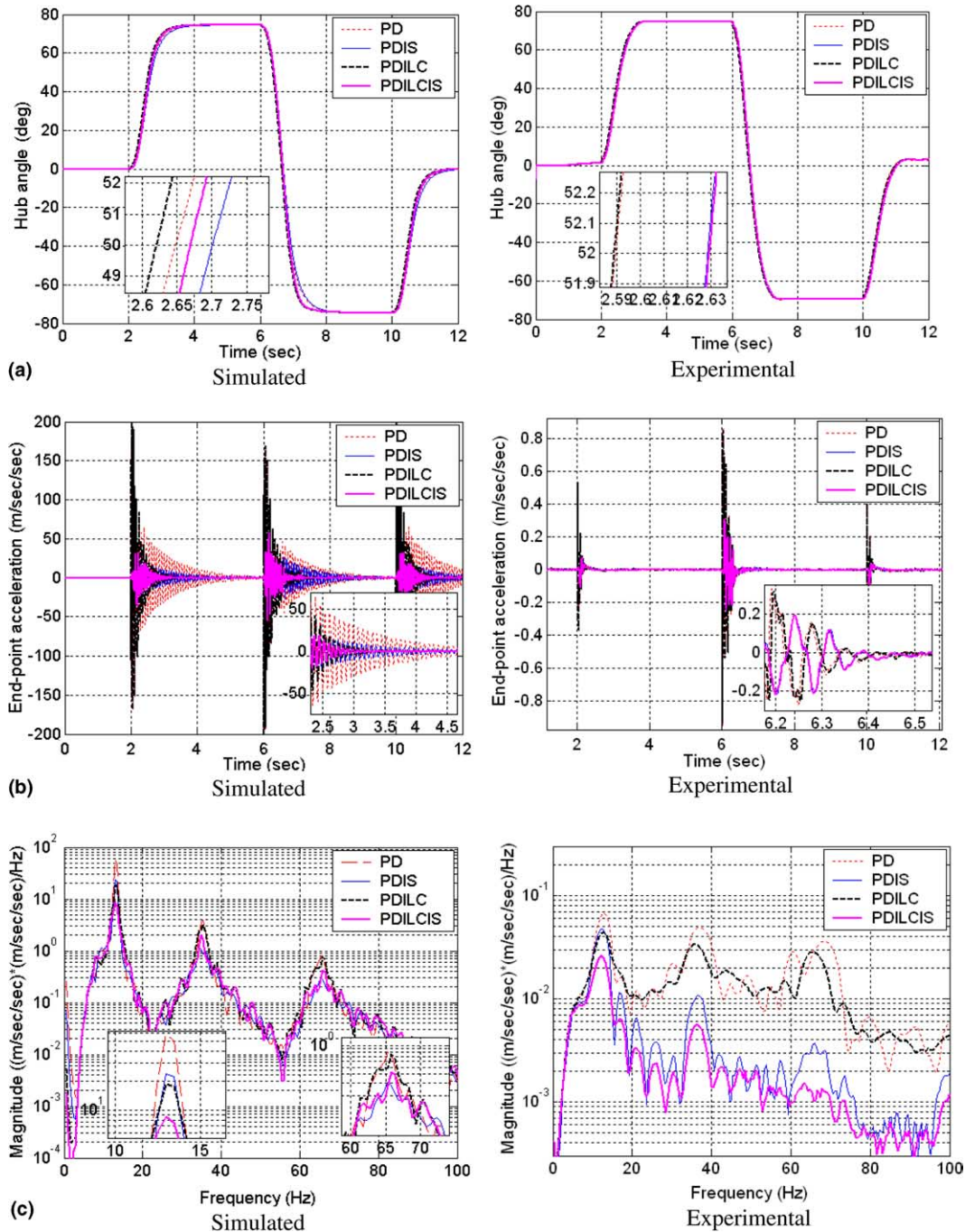
Fig. 10. Response of the simulated and experimental manipulator system without payload: (a) hub-angle (time domain); (b) end-point acceleration (time domain); (c) SD of end-point acceleration.

gence as a function of generations and the parameter values used in the GA, respectively. The corresponding responses of the manipulator without payload and with a 30 g payload with PD-ILC are shown in Figs. 10 and 11. It is noted that the proposed hybrid controller with learning algorithm is capable of reducing the system vibration while resulting in better input tracking performance. The vibration of the system settled within less than 3 s, which is much less than that achieved with PD control. The closed-loop system parameters with the PD control will subsequently be used to design

and evaluate the performance of ILC and feedforward control schemes in terms of input tracking capability and level of vibration reduction.

In the case of the hybrid learning and feedforward control scheme (PD-ILC-IS), an input shaper was designed based on the dynamic behaviour of the closed-loop system obtained using only the PD control. The corresponding responses of the manipulator without payload and a 30 g payload with PD-IS and PD-ILC-IS are shown in Figs. 10 and 11. As shown in the previous section, the natural
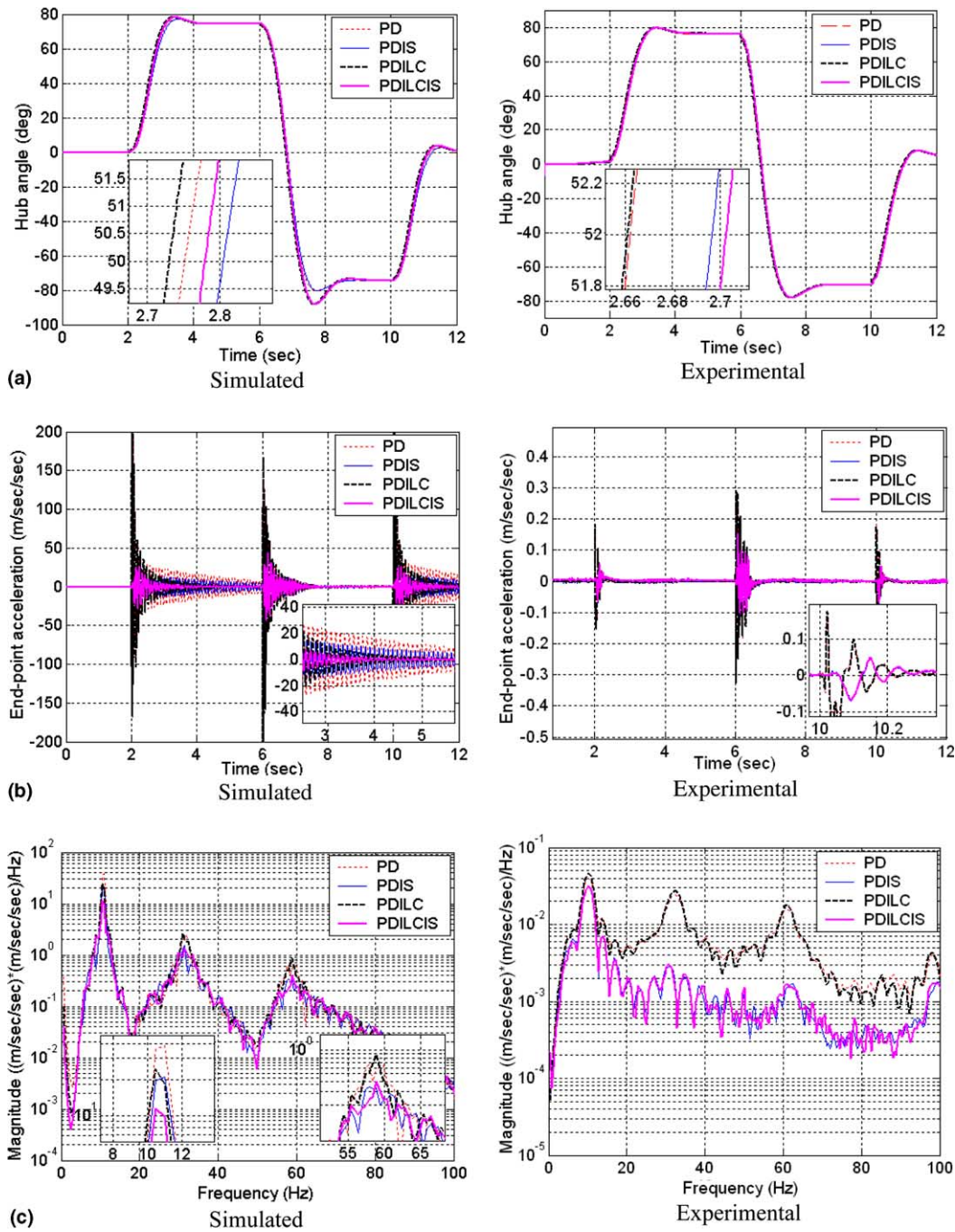
Fig. 11. Response of the simulated and experimental manipulator system with 30 g payload: (a) hub-angle (time domain); (b) end-point acceleration (time domain); (c) SD of end-point acceleration.

frequencies of the manipulator were 13, 35 and 65 Hz without payload and 11, 33 and 60 Hz with a 30 g payload. Previous experimental results have shown that the damping ratio of the flexible manipulator rangers from 0.024 to 0.1 [11]. The magnitudes and time locations of the impulses were obtained by solving Eq. (9) for the first three modes.

For digital implementation of the input shaper, locations of the impulses were selected at the nearest sampling time. In this case, the locations of the second impulse were obtained at 0.042 s, 0.014 s and 0.008 s for the three modes, respectively. The developed input shaper was then used to

pre-process the input reference shown in Fig. 7. The resulting responses of manipulator without payload with PD-IS and PD-ILC-IS are shown in Figs. 10 and 11. It is noted that the proposed hybrid controllers were capable of significantly reducing the vibration of the manipulator.

It is noted in the results presented above that a significant amount of vibration reduction was achieved at the end-point of the manipulator with the control schemes. With PD-ILC-IS control, maximum reduction at the end-point acceleration was achieved as compared to the other three methods. Moreover, the vibration of the system
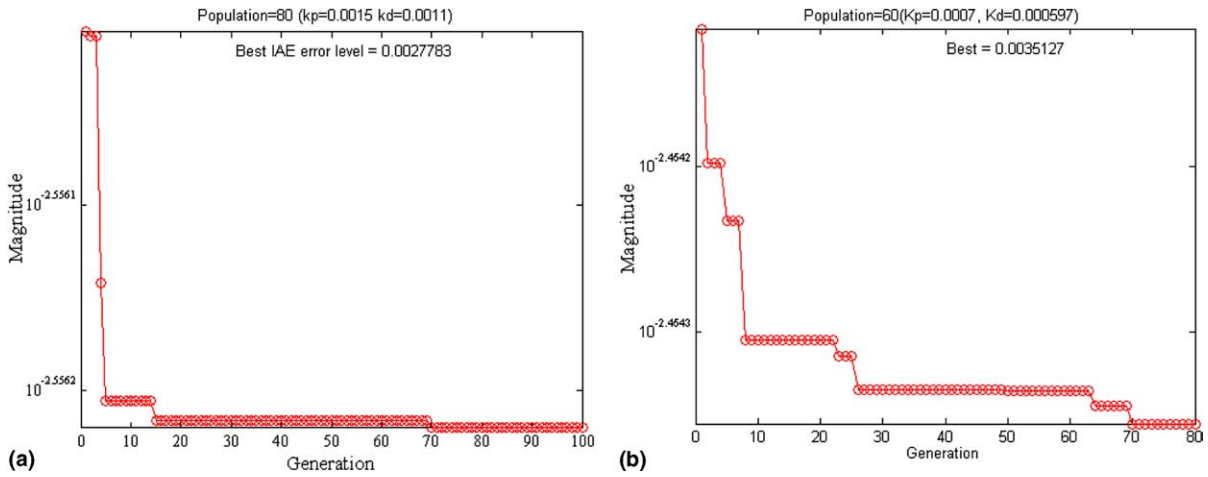
Fig. 12. Objective value vs number of generation (simulated system): (a) without payload; (b) with 30 g payload.
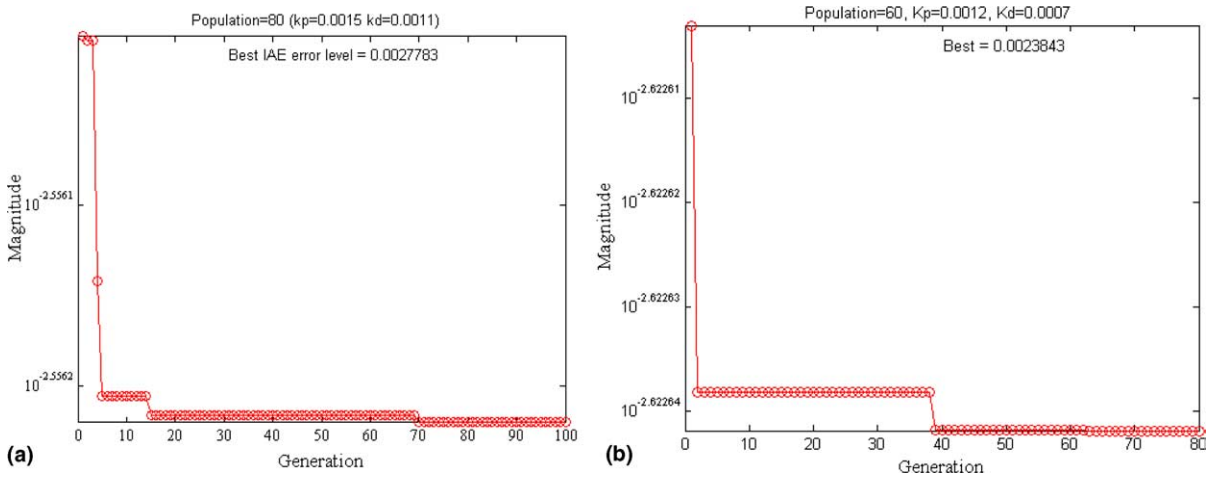

Fig. 13. Objective value vs number of generation (experimental system): (a) without payload; (b) with 30 g payload.

Table 1
GA parameters for PD-type learning

Parameter	Setting
Generation gap	0.9
Precision	14
Crossover rate	0.8
Mutation rate	0.025

settled within 3 s, which is better as compared with PD-IS. This is also evidenced in the SD of the end-point accelera-

tion, which shows lower magnitudes at the resonance modes. For the manipulator with a 30 g payload, a similar trend of improvement is observed. The performance of the controller at input tracking control was maintained similar to PD-ILC control. Moreover, the controllers were found to be able to handle vibration of the manipulator with a payload, as significant reduction in system vibration was observed. Furthermore, the closed-loop systems required only 3 s to settle down. This is further evidenced in Figs. 14–17, which show the level of vibration reduction with
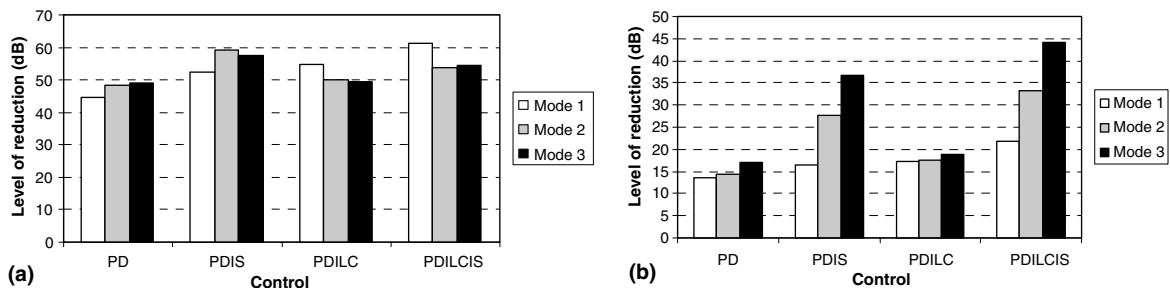

Fig. 14. Vibration reduction with the control techniques and the manipulator without payload: (a) simulated; (b) experimental.
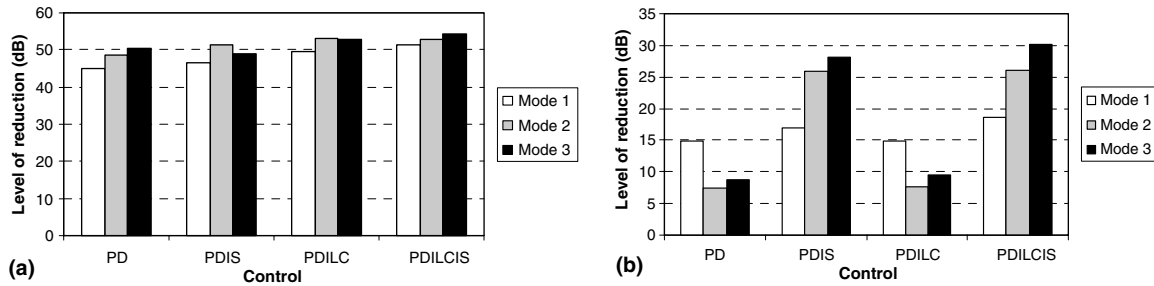
Fig. 15. Vibration reduction with the control techniques and the manipulator with 30 g payload: (a) simulated; (b) experimental.
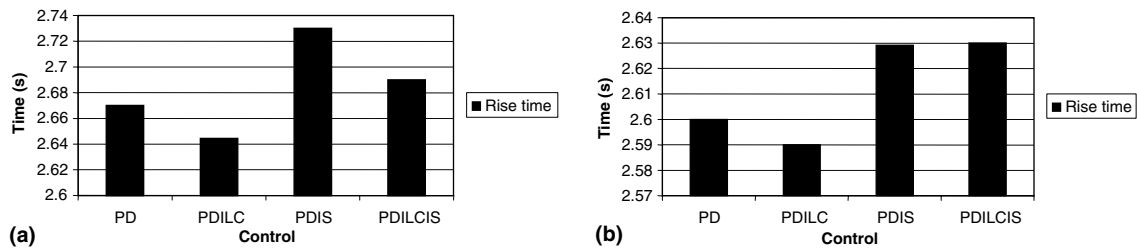

Fig. 16. Rise time of the hub angle response with the control techniques and the manipulator without payload: (a) simulated; (b) experimental.
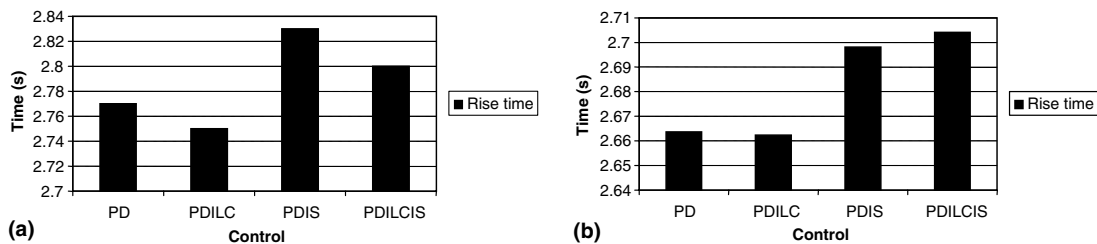

Fig. 17. Rise time of the hub angle response with the control techniques and the manipulator with 30 g payload: (a) simulated; (b) experimental.

the end-point acceleration responses at the resonance modes of the closed loop systems as compared to open loop and response rise time for the manipulator.

5. Conclusions

The development of hybrid learning control schemes for input tracking and vibration suppression of a flexible manipulator has been presented. The control schemes have been developed on the basis of collocated PD with ILC based on GA optimization and input shaping. The control schemes have been implemented and tested within the simulation and experimental environments of a single-link flexible manipulator without and with a payload. The performances of the control schemes have been evaluated in terms of input tracking capability and vibration suppression at the resonance modes of the manipulator. Acceptable input tracking control and vibration suppression have been achieved with both control strategies. A comparative assessment of the control techniques has shown that hybrid PD-ILC-IS scheme results in better performance than the PD-IS control in respect of hub-angle response

and vibration suppression of the manipulator. However, the system response rise time is longer in each case as compared to PD-ILC.

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