Sensors & Transducers, Vol. 179, Issue 9, September 2014, pp. 66-71

Sensors & Transducers

Optimal Control Using Instantaneous Optimal and Iterative Learning Control

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Received: 22 May 2014 /Accepted: 29 August 2014 /Published: 30 September 2014

Abstract: By combining instantaneous optimal control and iterative learning control (ILC), one new hybrid control strategy called instantaneous optimal iterative learning control is proposed. The linear system is chosen as the model for the new control strategy, and the quadratic performance function of the system is chosen as the objective function to be minimized. During the process of controlling responses of the system, the core idea of the iterative learning control is introduced in order to modify the control signals. By introducing the norms of matrices, the sufficient condition of convergence for the new control strategy is established in the paper. The model of a 20-floor building in the second generation benchmark vibration control is selected for numerical simulation. In the numerical simulation, the north-south component of the El wave is introduced as the excitation. Comparing to the instantaneous optimal control, results of the simulation show that instantaneous optimal iterative learning control improves the effectiveness. *Copyright © 2014 IFSA Publishing, S. L.*

Keywords: Instantaneous optimal control, Iterative learning control, Seismic response, Performance function.

1. Introduction

The dynamic responses arise while the high-rise structures are undergoing external excitations such as earthquakes, wind loads etc. Among the various external excitations which high-rise structures may experience, intense earthquakes always bring out safety problems of structures. For decades, scholars and engineers have focused on the techniques of eliminating the excessive dynamic responses and improving the comfort of high-rise structures. Till now, three kinds of techniques on reducing the dynamic responses of structures undergoing earthquakes are developed, which are passive control, active control and semi-active control. For active and semi-active control, optimal control algorithms are essential. Up to present, many effective control algorithms have been established, such as linear quadratic optimal control (LQR), H2 control, instantaneous optimal control (IOC) [1-3], fuzzy logic control and so on. Several of these control algorithms have been applied in actual structures.

Among these various algorithms of control, instantaneous optimal control has been paid much attention to [4] for its simple formulation and effectiveness in active control without solving the Ricatti equation. On the other hand, The IOC algorithm is derived basing on instantaneous quadratic performance function, in which, weighting matrices Q and R must be determined firstly. As is known, the performance of the IOC algorithm depends on the performance function. The efficiency of control descends rapidly, while inappropriate weighting matrices are selected. How to improve the adaptability of the weighting matrices when using the IOC algorithm appears to be a key problem.

Iterative learning control (ILC) getting error information by self learning is a branch of intelligent

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control. During self learning and getting error information, this intelligent control can produce feedback signals for the control system which may improve the efficiency of control. Iterative learning control can be traced back to 1978, in which year Uchiyama [5] presented the initial explicit formulation of ILC in Japanese, and Arimoto [6] et al, first introduced this control method in English, in 1984. The essential thought of iterative learning control is modifying the control signals by considering the error information between the values of outputs and the desired outputs. Youqing Wang [7] et al, studied and compared three kinds of control methods including ILC, RC and R2R, then the authors pointed out that ILC was a hot filed. Smolders [8] et al. proposed a nonlinear iterative learning approach based on model. Cueli [9] proposed a control method named iterative nonlinear model predictive control by combining iterative learning control and nonlinear model predictive control. As it can be seen, iterative learning control is mainly used in the machinery industry, but seldom used in civil engineering. While civil engineering structures are undergoing external excitation such as earthquakes, winds etc. uncertainties exist because of the uncertainties of both model itself and the external excitations. Generally, traditional optimal control algorithms use the outputs of the structure as the feed-back signals for determining the control signals without the feed-forward signals and also the ability of modifying the online control signals.

In the present paper, a new control algorithms combining instantaneous optimal control and iterative learning control calling ILC_IOC is proposed. Results of the numerical simulation prove that, the new strategy shows better control efficiency and robustness.

2. Derivation of the Control Law

In a general form, the vector equation of motion of an n degree of freedom linear system, subjected to an external excitation and control forces, can be written as:

$$M \cdot \ddot{x} + C \cdot \dot{x} + K \cdot x = H \cdot u + \Gamma \cdot \ddot{x}_g , \qquad (1)$$

The state-space representation of the above equation can be expressed as:

$$\dot{z} = A \cdot z + B \cdot u + E \cdot \ddot{x}_g , \qquad (2)$$

where $A = [-M_{-1}^{0} \cdot K - M_{-1}^{I} \cdot C]$, $B = [M_{-1}^{0} \cdot H]$, $E = [M_{-1}^{0} \cdot \Gamma]$.

By assuming $\tilde{A} = \exp(A \cdot \Delta t)$, $\tilde{B} = \int_0^{\Delta t} \exp(A \cdot \Delta t) dt \cdot B$, $\tilde{E} = \int_0^{\Delta t} \exp(A \cdot \Delta t) dt \cdot E$, the discrete state-space equation of equation (1) can be expressed as:

$$z(k+1) = \tilde{A} \cdot z(k) + \tilde{B} \cdot u(k) + \tilde{E} \cdot \ddot{x}_g(k) , \qquad (3)$$

The instantaneous quadratic performance function of equation (3) can be introduced.

$$J(k+1) = \frac{1}{2}[z^T(k+1) \cdot Q \cdot z(k+1) + u^T(k) \cdot R \cdot u(k)] , \qquad (4)$$

By combining equation (3) and (4), the Hamiltonian function can be get as follows:

$$H = \frac{1}{2}[z^T(k+1) \cdot Q \cdot z(k+1) + u^T(k)] + \lambda^T(k+1[\tilde{A} \cdot z(k) + \tilde{B} \cdot u(k) + \tilde{E} \cdot \ddot{x}_g(k) - z(k+1)] , \qquad (5)$$

Using the Minimal value principle, equations can be got as follows:

$$\begin{cases} \dfrac{\Delta H}{\Delta z(k+1)} = Q \cdot z(k+1) - \lambda(k+1) = 0 \\ \dfrac{\Delta H}{\Delta u(k)} = R \cdot u(k) + \tilde{B} \cdot \lambda(k+1) = 0 \\ \dfrac{\Delta H}{\Delta \lambda(k+1)} = \tilde{A} \cdot z(k) + \tilde{B} \cdot u(k) + \tilde{E} \cdot \ddot{x}_g(k) = z(k+1) \end{cases} , \qquad (6)$$

In reality, the excitation loads such as earthquakes, winds etc. can not be predicted, then, while getting the optimal control signals, the excitations are ignored. We can get the optimal control signals as follows:

$$u(k) = -(R + \tilde{B}^T \cdot Q \cdot \tilde{B})^{-1} \tilde{B}^T \cdot Q \cdot \tilde{A} \cdot z(k) , \qquad (7)$$

By substituting Eq.7 into Eq.3, one obtains responses of the system as follows:

$$z(k+1) = [\tilde{A} - \tilde{B} \cdot (R + \tilde{B}^T \cdot Q \cdot \tilde{B})^{-1} \cdot \tilde{B}^T \cdot Q \cdot \tilde{A}] \cdot z(k) + \tilde{E} \cdot \ddot{x}_g(k) , \qquad (8)$$

For the given system, the weighting matrixes Q and R in the performance function are firstly preset, then the control signals are decided by the feedback and can not be modified by the algorithm itself. In order to improve the fault tolerance of the optimal control algorithm, the iterative learning control (ILC) is introduced. The ILC is one kind of intelligent control algorithm, and can modify the control signals during the process of control itself.

One can assume the following equations:

$$\Gamma = -(R + \tilde{B}^T \cdot Q \cdot \tilde{B})^{-1} \cdot \tilde{B}^T \cdot Q \cdot \tilde{A}, \quad (9)$$

$$\Phi = [\tilde{A} - \tilde{B} \cdot (R + \tilde{B}^T \cdot Q \cdot \tilde{B})^{-1} \cdot \tilde{B}^T \cdot Q \cdot \tilde{A}], \quad (10)$$

Then Eq.7 and Eq.8 can be transferred into the following forms.

$$u(k) = \Gamma \cdot z(k), \quad (11)$$

$$z(k+1) = \Phi \cdot z(k) + \tilde{E} \cdot \ddot{x}_g(k), \quad (12)$$

The external excitations $\tilde{E} \cdot \ddot{x}_g(k)$ are ignored during the process of iterative for the signals of excitations can not be predicted. One can use the subscript *i* to stand for the step of iteration.

One can assume the initial state vector and control signal vector as following:

$$z_0(k) = z(k), \quad (13)$$

$$u_0(k) = \Gamma \cdot z_0(k), \quad (14)$$

The desired state vector for the high-rise structure undergoing earthquake is $z_d = \{0\}$, then the variation of state vector during the iterative can be written as follows:

$$\hat{z}_i(k+1) = e_i(k+1) = z_i(k+1) - z_d(k+1), \quad (15)$$

According to Eq. 15, Eq. 14 can be known as the variation of the control signals during the iterative process:

$$\begin{aligned}\hat{u}_i(k) &= u_i(k) - u_{i-1}(k) \\ &= \Gamma \cdot [z_i(k+1) - z_d()k+1]\end{aligned}, \quad (16)$$

Till now, the iterative learning control can be transferred into the standard form:

$$u_i(k) = u_{i-1}(k) + \Gamma \cdot e_i(k+1), \quad (17)$$

Eq.17 can also be written as follows:

$$u_n(k) = u_0(k) + \Gamma \cdot \int_{i=1}^{n} e_i(k+1), \quad (18)$$

where n stand for the last step of the iterative learning control.

Responses of the system undergoing the control signals of Eq.18 can be written as follows:

$$z(k+1) = \tilde{A} \cdot z(k) + \tilde{B} \cdot u_n(k) + \tilde{E} \cdot x_g(k), \quad (19)$$

3. The Convergence Analysis

First, three hypotheses are introduced as follows:

Hypothesis 1: The desired control signals are bounded, $\max_{1 \le k \le n} \|u_d(k)\| \le b_{u_d}$, where b_{u_d} is a positive constant;

Hypothesis 2: The external excitations are bounded, $\max_{1 \le i \le n} . \max_{1 \le k \le n} \|\tilde{E} \cdot \ddot{x}_{g,i}(k)\| \le b_\beta$, where b_β is a positive constant;

Hypothesis 3: During every step of iteration, the trajectory starts from the neighborhood of $z_d(0)$, $\|z_d(0) - z_i(k)\| \le b_{q_0}$, where b_{q_0} is a positive constant.

Basing on the above three hypotheses, one supposes $\|\tilde{A}\| = b_{\tilde{A}}$, $\|\tilde{B}\| = b_{\tilde{B}}$, $\|\Gamma\| = b_\Gamma$, $\|\Gamma \cdot \tilde{A}\| = b_{\Gamma \cdot \tilde{A}}$.

By considering Eq.3, and assuming:

$$\hat{z}_i(k+1) = z_d(k+1) - z_i(k+1),$$
$$\hat{u}_i(k) = u_d(k) - u_i(k),$$

one can get the following equation:

$$\hat{z}_i(k+1) = \tilde{A} \cdot z_i(k) + \tilde{B} \cdot u_i(k) - \tilde{E} \cdot \ddot{x}_g(k), \quad (20)$$

By considering the hypothesis 1 and 2, one can get the following equation:

$$\|\hat{z}_i(k+1)\| \le b_{\tilde{A}} \cdot \|\hat{z}_i(k)\| + b_{\tilde{B}} \cdot \|\hat{u}_i(k)\| + b_\beta, \quad (21)$$

By considering the hypothesis 3 and Eq.21, one gets the follow equation:

$$\|\hat{z}_i(k+1)\| \le \sum_{j=0}^{k-1} b_{\tilde{A}}^{k-1-j} \cdot (b_{\tilde{B}} \cdot \|\hat{u}_i(k)\| + b_\beta) + b_{\tilde{A}}^k \cdot b_{q_0}, \quad (22)$$

By Considering the ILC algorithm as Eq.23, one gets Eq.24.

$$u_i(k) = u_{i-1}(k) + \Gamma \cdot e_i(k+1), \quad (23)$$

$$\begin{aligned}\hat{u}_{i+1}(k) &= u_d(k) - u_{i+1}(k) \\ &= u_d(k) - u_i(k) - \Gamma \cdot e_i(k+1) \\ &= \hat{u}_i(k) - \Gamma \cdot [z_d(k+1) - z_i(k+1)] \\ &= \hat{u}_i(k) - \Gamma \cdot [\tilde{A} \cdot \hat{z}_i(k) + \tilde{B} \cdot \hat{u}_i(k) - \tilde{E} \cdot \ddot{x}_g(k)] \\ &= [\mathrm{I} - \Gamma \cdot \tilde{B} \cdot \hat{u}_i(k) - \Gamma \cdot \tilde{A} \cdot \hat{z}_i(k) - \Gamma \cdot \tilde{E} \cdot \ddot{x}_g(k)]\end{aligned}, \quad (24)$$

By considering hypothesis 2 and 3, one gets Eq.25.

$$\begin{aligned}\left\|\hat{u}_{i+1}(k)\right\| \le \left\|\mathrm{I}-\Gamma\cdot\tilde{B}\right\|\cdot\left\|\hat{u}_i(k)\right\| + \\ b_{\Gamma\cdot\tilde{A}}\cdot\left\|\hat{z}_i(k)\right\| + b_\Gamma\cdot b_\beta\end{aligned}, \quad (25)$$

By assuming $\rho = \left\|\mathrm{I}-\Gamma\cdot\tilde{B}\right\|$, and substituting Eq.23 and 24 into Eq.25, one gets the following equation.

$$\begin{aligned}&\left\|\hat{u}_{i+1}(k)\right\| \le \rho\cdot\left\|\hat{u}_i(k)\right\| + b_{\Gamma\cdot\tilde{A}}\cdot b_{\tilde{A}}^k\cdot b_{q_0} + b_\Gamma\cdot b_\beta \\ &+b_{\Gamma\cdot\tilde{A}}\left[\sum_{j=0}^{k-1} b_{\tilde{A}}^{k-1-j} b_{\tilde{B}}\cdot\left(\left\|\hat{u}_i(k)\right\| + b_\beta\right)\right]\end{aligned}$$

For the above equation, one multiplies $(1/\lambda)^k$ on both sides, and the λ norm is got.

$$\begin{aligned}&\left\|\hat{u}_{i+1}(k)\right\|\cdot\left(\frac{1}{\lambda}\right)^k \le \rho\cdot\left\|\hat{u}_i(k)\right\|\cdot\left(\frac{1}{\lambda}\right)^k + b_{\Gamma\cdot\tilde{A}}\cdot b_{q_0} \\ &\cdot\left(\frac{b_{\tilde{A}}}{\lambda}\right) + b_\Gamma\cdot b_\beta\cdot\left(\frac{1}{\lambda}\right)^k + \left(\frac{b_{\Gamma\cdot\tilde{A}}}{\lambda}\right) \\ &\cdot\sum_{j=0}^{k-1}\left(\frac{b_{\tilde{A}}}{\lambda}\right)^{k-1-j}\cdot\left(b_{\tilde{B}}\cdot\left\|\hat{u}_i(j)\right\|\left(\frac{1}{\lambda}\right)^j + b_\beta\right)\end{aligned}, \quad (26)$$

By assuming $\lambda > \max\{1, b_{\tilde{A}}\}$ d, one gets Eq.27.

$$\begin{aligned}&\left\|\hat{u}_{i+1}(k)\right\|_\lambda \le \rho\cdot\left\|\hat{u}_i(k)\right\|_\lambda + b_{\Gamma\cdot\tilde{A}}\cdot b_{q_0} + b_\Gamma\cdot \\ &b_\beta + \left(b_{\tilde{B}}\cdot\left\|\hat{u}_i(k)\right\|_\lambda + b_\beta\right)\cdot\frac{b_{\Gamma\cdot\tilde{A}}\cdot[1-(b_{\tilde{A}}/\lambda)^n]}{\lambda - b_{\tilde{A}}}\end{aligned}, \quad (27)$$

By assuming the following equations:

$$\tilde{\rho} = \rho + \frac{b_{\tilde{B}}\cdot b_{\Gamma\cdot\tilde{A}}\cdot[1-(b_{\tilde{A}}/\lambda)^n]}{\lambda - b_{\tilde{A}}}$$

$$\varepsilon = b_{\Gamma\cdot\tilde{A}}\cdot b_{q_0} + b_\Gamma\cdot b_\beta + \frac{b_\beta\cdot b_{\Gamma\cdot\tilde{A}}\cdot[1-(b_{\tilde{A}}/\lambda)^n]}{\lambda - b_{\tilde{A}}}$$

and considering Eq. 27, one gets Eq. 28.

$$\left\|\hat{u}_{i+1}(k)\right\|_\lambda \le \tilde{\rho}\cdot\left\|\hat{u}_i(k)\right\|_\lambda + \varepsilon, \quad (28)$$

Basing on Eq. 28, one can get the following equation.

$$\left\|\hat{u}_{i+1}(k)\right\|_\lambda \le \tilde{\rho}^i\cdot\left\|\hat{u}_i(k)\right\|_\lambda + \frac{\varepsilon\cdot(1-\tilde{\rho}^i)}{1-\tilde{\rho}}, \quad (29)$$

While assuming λ be large enough, and $\tilde{\rho}\approx\rho<1$, one gets Eq. 30.

$$\lim_{i\to\infty}\left\|\hat{u}_i(k)\right\|_\lambda \le \frac{\varepsilon}{1-\tilde{\rho}}, \quad (30)$$

For Eq. 22, one multiplies $(1/\lambda)^k$ on both sides, and the λ norm is got.

$$\begin{aligned}&\left\|\hat{z}_i(k)\right\|\cdot\left(\frac{1}{\lambda}\right)^k \le \frac{1}{\lambda}\cdot\sum_{j=0}^{k-1}\left(\frac{b_{\tilde{A}}}{\lambda}\right)^{k-1-j}\cdot \\ &\left(b_{\tilde{B}}\cdot\left\|\hat{u}_i(k)\right\|\cdot\left(\frac{1}{\lambda}\right)^j + b_\beta\cdot\left(\frac{1}{\lambda}\right)^j\right) + \left(\frac{b_{\tilde{A}}}{\lambda}\right)^k\cdot b_{q_0}\end{aligned}, \quad (31)$$

For the conditions of $b_\beta\cdot\left(\frac{1}{\lambda}\right)^j \le b_\beta$, $\frac{b_{\tilde{A}}}{\lambda} < 1$, one can get Eq.32.

$$\left\|\hat{z}_i(k)\right\|_\lambda \le \frac{b_{\tilde{B}}\cdot\left[1-\left(\frac{b_{\tilde{A}}}{\lambda}\right)^n\right]}{\lambda - b_{\tilde{A}}}\left\|\hat{u}_i(j)\right\|_\lambda\frac{b_\beta\cdot\left[1-\left(\frac{b_{\tilde{A}}}{\lambda}\right)^n\right]}{\lambda - b_{\tilde{A}}}\cdot b_{q_0}, \quad (32)$$

By instituting Eq. 30 into Eq. 32, one gets the following equation.

$$\begin{aligned}&\lim_{i\to\infty}\left\|\hat{z}_i(k)\right\|_\lambda \le \frac{b_{\tilde{B}}\cdot\left[1-\left(\frac{b_{\tilde{A}}}{\lambda}\right)^n\right]}{\lambda - b_{\tilde{A}}}\cdot\frac{\varepsilon}{1-\tilde{\rho}}, \\ &+\frac{b_\beta\cdot\left[1-\left(\frac{b_{\tilde{A}}}{\lambda}\right)^n\right]}{\lambda - b_{\tilde{A}}} + b_{q_0}\end{aligned} \quad (33)$$

Basing on Eq. 30 and Eq. 33, one gets the conclusion that $\left\|\hat{u}_i(k)\right\|_\lambda$ and $\left\|\hat{z}_i(t)\right\|_\lambda$ is bounded by b_β and b_{q_0}. The sufficient condition for the system expressed by Eq. 18 and Eq. 19 can be indicated as Eq. 34.

$$\rho = \left\|I - C\cdot B\cdot\Gamma\right\| < 1, \quad (34)$$

where I is the unit matrix.

4. Numerical Simulation

In this section, a numerical simulation using the new control strategy presented in the previous section is carried out. The Benchmark II model which is a 20-story steel structure is taken into account. The structure was designed by Brandow and Johnston Associates for the SAC Phase II Steel Project. Although not actually constructed, the structure meets seismic code and represents a typical mid- to high-rise building. The structure is 30.48 m by 36.58 m in plan, and 80.77 m in elevation. The bays are 6.10 m on center, in both directions, with five bays in the north-south (N-S) direction and six bays in the east-west (E-W) direction. By Guyan reduction, one obtains the 20 DOFs model [10], in which the lumped masses and stiffness are:

$m_1=1.126\times10^6$ kg, m_2~$m_{19}=1.1\times10^6$ kg, $m_{20}=1.170\times10^6$ kg, k_1~k_5=862 070 kN/m, k_6~k_{11}=554 170 kN/m, k_{12}~k_{14}=453 510 kN/m, k_{15}~k_{17}=291 230 kN/m, k_{18}~k_{19}=256 460 kN/m, k_{20}=171 700 kN/m.

The damping ratio is assumed to be 0.02, and the damping matrix is constructed in RayLeigh damping.

Consider active tendon system as the active control system for the structure. In order to compare the efficiency of the new control strategy with the traditional instantaneous optimal control, three models are loaded to the NS component of 1940El earthquake, which gets a peak acceleration of 3.147 m/s^2, and the duration of the component is 10 s.

The peak responses of displacements, velocity, accelerations and story drifts are plotted in Fig. 1, Fig. 2, Fig. 3 and Fig. 4.

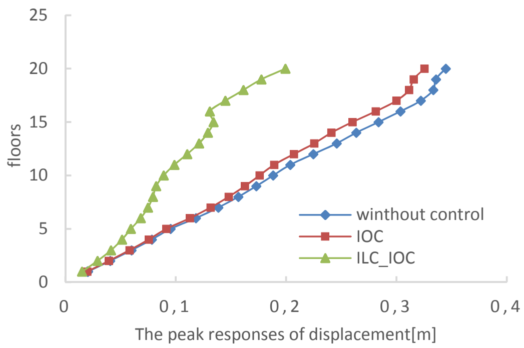

Fig. 1. The peak responses of displacement.

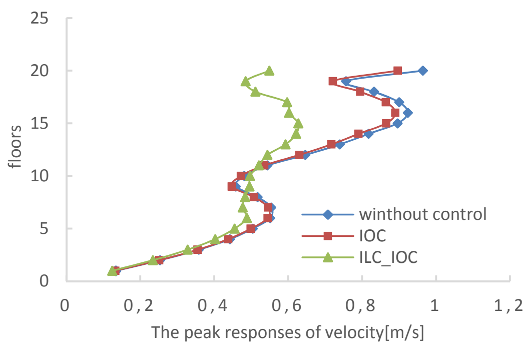

Fig. 2. The peak responses of velocity.

Fig. 1 shows that the new control strategy improves the control efficiency of displacements apparently, especially at high floors. The new control strategy shows the similar control efficiency in controlling the responses of velocity like it does in controlling the responses of displacements, except at the 9th and 10th floor. According to Fig. 3, one may find that both instantaneous optimal control and the new control strategy proposed in the above section do not reduce the acceleration responses obviously. Fig. 4 shows that the new control strategy improves the control efficiency of story drifts except at the 19th and 20th floor.

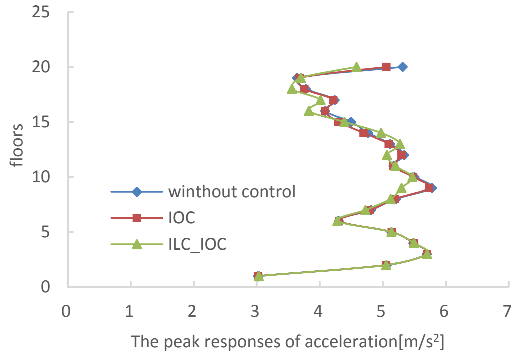

Fig. 3. The peak responses of acceleration.

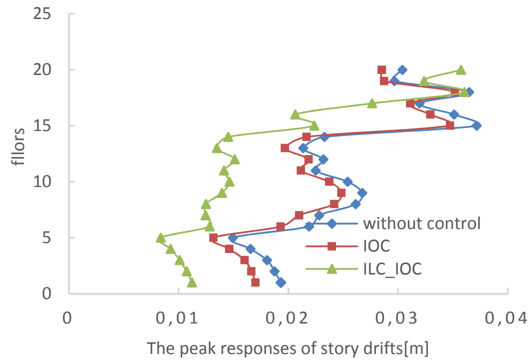

Fig. 4. The peak responses of story drifts.

5. Conclusions

A new hybrid control strategy, named ILC_IOC, based on instantaneous optimal control and iterative learning control was presented. The new control strategy was derived from the error model of state equation and the instantaneous quadratic form of performance function. During the period of control, the control forces were first obtained from the traditional instantaneous optimal control algorithm, and then, modified by iterative learning control algorithm, during the process of modifying, the amplitudes of control forces were modified. The sufficient condition for the new hybrid control strategy is derived.

The Benchmark II model was selected as the model for simulating, and the N-S component of the 1940 El wave was selected as the input load. Results of the numerical simulation showed that, comparing to the traditional instantaneous optimal control algorithm, the new hybrid control strategy showed to be more effective, especially in the responses of displacement and inter-story drift at high floors.

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