Input space dependent controller for civil structures exposed to multi-hazard excitations

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Abstract
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Keywords
Semi-active damping, Input space, Data-driven control, Time delay feedback control, Modified Friction Device, Embedding Theorem, Structural control, Multi-hazard

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Input space dependent controller for civil structures exposed to multi-hazard excitations

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ABSTRACT

A challenge in the control of civil structures exposed to multiple types of hazards is in the tuning of control parameters to ensure a prescribed level of performance under substantially different excitation dynamics, which could be considered as largely uncertain. A solution is to leverage data driven control algorithms, which, in their adaptive formulation, can self-tune to uncertain environments. The authors have recently proposed a new type of data-driven controller, termed input space dependent controller (ISDC), that has the particularity to adapt its input space in real-time to identify key measurements that represent the essential dynamics of the system. Previous studies have focused on time delay formulations, where the adaptive control rule would use time delayed measurements as inputs. In this configuration, termed variable multi-delay controller (VMDC), the time delay itself was adaptive, which provided the input space dependence capabilities. However, the size, or embedding dimension, of the input space was kept constant. In this paper, the authors formulate and study a strategy to also have the embedding dimension vary, therefore providing full adaptive input space capabilities. This generalization of the ISDC algorithm will allow the controller to adapt to excitations with higher levels of chaos, such as a seismic event. The performance of ISDC under multi-hazard excitations is first investigated on a single-degree-of-freedom system and compared with the previously developed and demonstrated VMDC. Results show that the adaptive embedding dimension provides significantly enhanced mitigation performance. After, the ISDC performance is assessed on two benchmark buildings equipped with a semi-active friction device and subjected to non-simultaneous multi-hazard excitations (wind, blast and earthquake). Results are compared with a sliding mode controller, where the ISDC is shown to provide better mitigation capabilities.

1. Introduction

Motion-based design of civil structures is a design methodology that consists of sizing structural mass, stiffness, and damping in order to restrict structural motion within a prescribed level of performance, while ensuring that structural components meet safety requirements [1]. The utilization of passive supplemental damping strategies [2–5] to meet such motion requirements is now widely accepted by the field of structural engineering. However, a limitation of passive systems is in their restricted performance bandwidth, which typically makes them applicable to single types of hazard only. A solution is to employ high-performance control systems (HPCSs), which include semi-active [6–8], hybrid [9–11] and active damping systems [12–14], that offer significantly higher controllability due to their mechanical or chemical adaptive capability. HPCS can therefore be used to protect structures against multiple simultaneous or non-simultaneous types of hazards, termed multi-hazards. Nevertheless, the performance of HPCS depends heavily on the design of the controller, which itself relies on the availability of sensor information and capability of actuation. Challenges associated with designing controllers for multi-hazards include: (1) uncertainties and large variabilities in the external excitation dynamics; (b) uncertainties in the dynamic properties of controlled structures; and (c) limited available measurements with non-negligible probabilities of sensor failure.

To address these multi-hazard control challenges, one can utilize model driven controllers (MDCs) or data driven controllers (DDCs). Typical MDCs include linear quadratic regulator (LQR) [15,16] and nonlinear Lyapunov-based controllers [17,18]. They have shown great
potential at providing robust mitigation capabilities, but they require some levels of knowledge about the system, such as the mass and stiffness parameters. It follows that MDCs may underperform when dynamic parameters are inaccurate or unknown [19,20]. Conversely, data-driven approaches rely on implicit information from measurements and do not require knowledge of system dynamics. These methods have been widely studied and applied in fault detection for example [21–23]. In the structural control field, typical DDCs include model-free adaptive controllers [24], fuzzy controllers [25], and neurocontrollers [26–28]. Generally, these controllers require some level of training through input-output examples, which is difficult to achieve when a wide range of excitation amplitudes, frequencies, and dynamics are considered.

Of interest to the authors are time delay controllers of the type

$$u(t) = \sum_{i=1}^{d} g_i y(t-(i-1)\tau) = G^T\nu$$

(1)

where \( u \) is the control force, \( y \) is an observation or input, \( \nu \in \mathbb{R}^{d\times 1} \) is the delay vector constructed from \( d \) observations delayed by \( \tau \), and \( g_i \) and \( G \in \mathbb{R}^{d\times 1} \) are the control gains and the control gain matrix, respectively, where \( g_i \) is necessarily a constant and could be obtained through a function. In work on time delay controllers, Pyragas first proposed a time delay autosynchronization (TDAS) control for stabilizing periodic orbits of a chaotic system [29], which showed limited performance for highly unstable periodic orbits. Socolar et al. [30] overcame this issue by proposing an extended TDAS (ETDAS) for the stabilization of systems with high frequency chaotic oscillations. While successful, it was discussed that the ETDAS could be more effective, because \( \tau \) was constant and could not be selected appropriately for unknown systems. Ahlborn and Parlitz [31] proposed a multiple delay feedback control (MDFC) with two or more numbers of delays \( d \). A good performance improvement was obtained, but the MDFC introduced a significant number of control parameters [32]. Instead of a constant time delay \( \tau \), Gjurchinovski and Urumov [33] proposed a variable delay feedback control (VDFC) for stabilizing unstable steady states. The time delay \( \tau \) is varied using a periodic function that oscillates around a nominal value. A limitation of the VDFC is that the nominal delay value needs to be pre-selected. Pyragas et al. [34] proposed an adaptive delayed feedback control where the time delay can be adapted continuously by the descent gradient method. The advantage of this controller is that a knowledge of the system (e.g. period of controlled orbit) is not required. However, the adaptive time delay method requires an initial time delay that is close to the optimal value [35].

A common feature of those time delay controllers is the reliance on an offline selection of \( \tau \) and \( d \). The ability to, instead, select these parameters online and in real-time would improve the performance of these controllers by tailoring their input-space to the excitation. In fact, the architecture of the input-space of DDC is often overlooked [36,37]. For instance, it was demonstrated by Hong et al. [38] that the optimal values of \( \tau \) and \( d \) merely remains constant throughout a high-rate dynamic event. A solution is to allow the input-space of a given DDC to vary with time. This idea, termed Input Space Dependent Controllers (ISDCs), was first proposed by Laflamme et al. [39]. The authors presented a sequential adaptive neurocontroller for which a time-varying delay vector was used as the input space. Later work in Ref. [40] studied a multi-delay controller based on a time-varying \( \tau \) selected online, while \( d \) was kept constant. This specialized type of ISDC was termed Variable Multi-Delay Controller (VMDC). Work included boundaries on the selection rule to ensure stability. In both cases, the online selection of parameters was based on the Embedding Theorem [41–43]. The theorem states that the essential dynamics of a stationary system can be represented by an optimal delay vector \( \nu^*(\tau^*,d^*) \), where the asterisk denotes an optimal value. The theorem has been initially developed for autonomous systems [41], and applied in many fields such as system identification and model prediction. See Refs. [44–46] for instance.

In this paper, we present a general formulation of the ISDC, which includes an online selection strategy for both \( \tau \) and \( d \). Unlike prior work from the authors in Ref. [39], the controller is based on a simple time delay formulation as shown in Eq. (1) where \( g_i \) are constants, in order for the focus to be on the selection of the input space itself. Unlike the work in Ref. [40], the embedding dimension \( d \) in this paper is also allowed to vary. It follows that, by varying both \( \tau \) and \( d \), the ISDC identifies in real time the essential dynamics found in the input space (from measurements) produced by different or combined hazards, and adapt its architecture accordingly for enhanced mitigation capabilities. Therefore, the ISDC can adapt to unknown excitation dynamics, including nonstationary systems, using local and limited measurements only enabling implementations through either wired or wireless communication protocols [47,48]. Note that due to its simple time delay formulation and limited dimensionality, the ISDC is computational efficient and can be used in real time, as demonstrated in prior work [39,40].

The upcoming section provides the background on the Embedding Theorem. The subsequent section presents the ISDC algorithm, which includes the adaptive rules for the control gains, and the time delay and embedding dimension selection rules. This is followed by studies of ISDC in a single-degree-of-freedom (SDOF) system to evaluate its performance under non-simultaneous multi-hazards excitations. The performance of the ISDC is compared with the previously developed VMDC. After, the ISDC is further evaluated on two benchmark buildings equipped with semi-active damping devices subjected to multi-hazard excitations. The results are summarized in the last section.

2. Background

This section introduces the Embedding Theorem that constitutes the basis of the ISDC, and presents the online adaptation rules for \( \tau \) and \( d \).

2.1. Embedding Theorem

Consider a SDOF system of the type

$$m\ddot{x}(t) + c\dot{x}(t) + kx(t) = u(t) + f(t) - ma_g(t)$$

(2)

where \( m, c, \) and \( k \) are the system’s mass, damping, and stiffness, respectively, \( x(t) \) is the displacement state, the dots represent time derivatives, \( u(t) \) is the control force from Eq. (1), \( f(t) \) is an external loading, and \( a_g(t) \) is ground acceleration, as illustrated in Fig. 1. For simplicity, the observation feedback \( y(t) \) (Eq. (1)) is taken as the displacement state \( y(t) = x(t) \). Assuming stationary inputs \( u_f \) and \( a_g \), the Embedding Theorem states that the unknown system (Eq. (2)) can be topologically reconstructed from a properly formulated delay vector \( \nu^*(t) \)

$$\nu^*(t) = [y(t-	au^*) \ y(t-(d^*-1)\tau^*)]$$

(3)

where \( \nu^*(t) \) preserves all of the system’s essential dynamics or topology. In other words, there exists a one-to-one (diffeomorphic) map between

Fig. 1. SDOF system.
the phase-space of the unknown system and the phase-space of the equivalent system represented by \( \nu^* \). This concept is illustrated in Fig. 2. Fig. 2(a) is the phase-space of the system’s response under a harmonic loading \( f(t) = \hat{f} \sin(\Omega t) \) of magnitude \( \hat{f} \) and frequency \( \Omega \). Fig. 2(b) is the time series measurement (observation) where \( y(t) = x(t) \). Fig. 2(c) shows the reconstructed phase-space from \( \nu^* \) where \( d^* = 2 \), as it should be for a harmonic signal [49]. The reconstructed phase space is topologically equivalent to the original system.

Because the optimal delay vector \( \nu^* \) preserves all of the system’s dynamics, it is argued that such a vector would provide a black-box controller with a near-optimal input-space, resulting in a minimal dimension of the representation, therefore minimizing the curse of dimensionality [50,51], and optimal computation time. The procedure to select \( \tau^* \) and \( d^* \) will be described in the upcoming subsections. Note that the Embedding Theorem does not apply to non-stationary systems, and the system of interest to the authors is non-stationary in nature, because of both the internal and external inputs. For instance, the control force may include an adaptive control rule, and a natural hazard cannot necessarily be modeled as a stationary process. Here, it is hypothesized that the utilization of a time-varying \( \nu^* \) can be equivalent to discretizing the nonstationary system into stationary systems of shorter duration, therefore enabling the application of the Embedding Theorem.

2.2. Optimal time delay selection

A typical strategy to select the optimal time delay \( \tau^* \) is based on Shannon’s information theory. The methodology consists of evaluating the level of mutual information (MI) [52] between two sets of observations. If the level of information is high, then the added observations are redundant. Conversely, if it is low, the added observations add information. The MI on a set of two observations \( f_i \) and \( f_j \) is given by

\[
\text{MI}(f_i, f_j) = -\sum_{i=1}^{n} p(f_i) \log_2 p(f_i) - \sum_{j=1}^{n} p(f_j) \log_2 p(f_j) + \sum_{i=1}^{n} \sum_{j=1}^{n} p(f_i, f_j) \log_2 p(f_i, f_j)
\]

where \( n \) is the length of the observations, \( p(\cdot) \) is the probability of an observation computed by classifying the last \( n \) observations into a predefined number of bins \( M_{\text{bin}} \), and \( p(\cdot, \cdot) \) is the joint probability between two sets of observations. The first local minima of the MI gives the optimal lowest level of information from a new set of observations or the optimal delay. Fig. 3 shows the MI test results between observation \( y(t) \) and delayed measurement \( y(t-\tau) \) for the example illustrated in Fig. 2. The MI value decreases with increasing time delay until it reaches the first local minimum point (0.13 s). The bottom of the figure plots the reconstructed phase-spaces using time delays \( \tau = 0.01, 0.07, 0.13, 0.2, 0.25 \) s. The phase-space is collapsed to a 45° line for small values of \( \tau \) (\( \tau = 0.01 \) s). As \( \tau \) increases, the reconstructed system starts to unfold (\( \tau = 0.07 \) s) until it reaches the first local minima of the MI test (0.13 s) marked by the red square. Beyond this point, the system starts folding back and loses information (\( \tau = 0.2 \) s and \( \tau = 0.25 \) s).

2.3. Optimal embedding dimension selection

Literature [53] showed that the most accurate method for determining the optimal embedding dimension is the false nearest neighbors (FNN) test proposed by Kennel et al. [49]. The method consists of evaluating the neighboring points in a given embedding dimension, and investigating if these points remain neighbors when the embedding dimension is increased. If points are no longer neighbors, then false neighbors are identified. The embedding dimension that provides a number of false neighbors that falls below a given threshold is taken as the optimal embedding dimension.

Mathematically, a false neighbor is detected if

\[
\frac{R_{d+1}(t, \tau) - R_d^2(t, \tau)}{R_d^2(t, \tau)} > A_{\text{th}}
\]

(5)

where \( R_d^2(t, \tau) \) is the Euclidean distance between measurement \( y(t) \) and its \( r \)-th nearest neighbor \( y^{(r)}(t) \) for an embedding dimension \( d \), and \( A_{\text{th}} \) is a user-defined threshold. An additional criterion needs to be satisfied to establish a false neighbor when the size of data is not sufficiently large

\[
\frac{R_{d+1}(t, \tau)}{R_d} > A_{\text{th}}
\]

(6)

where \( R_d \) is the standard deviation of the measurement \( y(t) \), and \( A_{\text{th}} \) is user defined threshold. Recommended parameter values for \( R_{\text{th}} \) and \( A_{\text{th}} \) are 10–20 and 2, respectively [54].

Fig. 4(a) is a plot of the FNN test results applied to the example illustrated in Fig. 2, for \( \tau^* = 0.13 \) s. The FNN percentage drops from 45% to 2% with the second criterion by increasing \( d \) from 1 to 2, showing that \( d = 2 \) is a sufficient embedding dimension. Fig. 4(b–d) graphically illustrates the results. Three points highlighted by a square, asterisk, and circle which appear to be neighbors are chosen in \( d = 1 \) (Fig. 4(b)). Once the embedding is increased to \( d = 2 \) (Fig. 4(c)), the circle is no longer a neighbor with the square and asterisk. The circle is considered a false nearest neighbor. Further increasing the embedding to \( d = 3 \) (Fig. 4(c)) maintains the topology of the system, and neighbors (square and asterisk points) remain neighbors, providing an unnecessary dimension (overembedding).
3. ISDC algorithm

The ISDC algorithm, schematized as an input-output system in Fig. 5, outputs a control force \( u(t) \) as a function of the input space \( \nu(t) \). Here, this function is an adaptive time delay formulation with control gains \( G(t) \) varying based on an error feedback. Remark that other representation types could be selected, including neural networks. The input space is also adaptive, which constitutes the novelty of the ISDC. This section presents the adaptive rules used for the adaptation of the input space and control gains, followed by a full description of the ISDC algorithm.

![Fig. 3. The mutual information test of measurement \( y(t) \) with its minimum (0.13 s) indicated by the red square and reconstructed phase space as a function of \( \tau \).](image)

![Fig. 4. (a) The percentage of false nearest neighbors in observation \( y(t) \) obtained from the second criterion of FNN test; reconstructed phase space with \( \tau = 0.13 \) s plotted with embedding dimensions (b) \( d = 1 \); (c) \( d = 2 \); and (d) \( d = 3 \).](image)
3.1. Delay vector (input space)

The delay vector \( v(t) \) is constructed through the selection of \( \tau \) and \( d \). Because of the longer computation time, a new delay vector is only constructed every \( i \) time interval (\( n \) steps) and maintained constant within the interval. The initial value \( \tau_0 \) is selected arbitrarily due to the lack of prior data, and \( d_i \) is taken as 2, being the smallest meaningful embedding dimension.

At the beginning of the \( i \)th time interval, \( \tau_i^* \) is computed using the MI test. A \( C^\infty \) transition function is generated to smoothly adapt \( \tau(t) \) towards \( \tau_i^* \) [28]:
\[
\beta(t) = \frac{1}{1 + e^{-\frac{t_i - t + \tau(t) \tau_i^*/2}{\tau_i^*/2}}}
\]  

(7) where \( t_i \) is the start time of the \( i \)th time interval, and \( \eta_1 \) and \( \eta_2 \) are constants with \( \eta_2 \) representing the length of the transition region, yielding
\[
\tau(t) = (1-\beta(t))\tau_{i-1}^* + \beta(t)\tau_i^*
\]  

(8) where \( \tau_{i-1}^* \) and \( \tau_i^* \) are the computed optimal time delays at corresponding time intervals \( i-1 \) and \( i \), respectively. \( \tau(t) \approx \tau_i^* \) when \( t \) is close to the next time interval \( i \) (\( \beta \approx 1 \)).

The optimal dimension \( d^* \) is computed based on the FNN test, and \( d(t) \) is limited to increment or decrement by one unit at the beginning of the \( i \)th time interval and keep constant to ensure robustness:
\[
d(t) = \begin{cases} 
   d(t-1) + \text{sgn}(d_i^*-d(t-1)) & \text{if } t = t_0(i) \\
   d(t-1) & \text{otherwise} 
\end{cases}
\]  

(9) where \( d_i^* \) is the computed optimal embedding dimension at corresponding time intervals \( i \), and \( \text{sgn} \) is the sign or sigmoid function.

A transition region is used to smoothly vary the dimension of the delay vector:
\[
y(t) = \begin{cases} 
   \beta(t)y(t) - d(t-1)\tau(t) & \text{if } d \text{ is increased} \\
   (1-\beta(t))y(t) - (d(t-1)-1)\tau(t) & \text{if } d \text{ is decreased} 
\end{cases}
\]  

(10) Note that a dimension can be removed from the representation once \( y(t) - d(t-1)\tau(t) \) falls below a given threshold.

3.2. Adaptive control gains

Consider the state space representation of SDOF system from Eq. (2), which could be used to extend the adaptation rule to multi degrees-of-freedom (MDOF) applications
\[
\dot{X}(t) = AX(t) + Bu(t) + B_f f(t) + B_\alpha \alpha(t)
\]  

(11) with:
\[
X(t) = \begin{bmatrix} x(t) \\ \dot{x}(t) \end{bmatrix}, \quad A = \begin{bmatrix} 0 & 1 \\ -\frac{\gamma \lambda}{\mu} & -\frac{\gamma}{\mu} \end{bmatrix}, \quad B_f = B_\alpha = \begin{bmatrix} 0 \\ 1 \end{bmatrix}
\]  

where \( X(t) \) is the state vector and \( u(t) = G(t)\nu(t) \) is the control force (Eq. (11)). A back-propagation rule is used to adapt gains \( G(t) \):
\[
G(t) = -\gamma \nu(t)\dot{\hat{A}}_b s(t)
\]  

(12) where \( \dot{\hat{A}}_b \) is an estimation of vector \( B_\alpha \Lambda = [1 \; \lambda] \) is a user-defined weight matrix that contains a strictly positive constant \( \lambda, \gamma \) is a positive definite diagonal matrix with equal adaptation weights \( \gamma, \lambda \) is a \( 2 \times 2 \) identity matrix, and \( s(t) \) is a sliding surface of the form [55]:
\[
s(t) = \Lambda e(t) = \Lambda (X(t)-X_d) = \Lambda X(t)
\]  

(13) where \( e(t) \) is the error between the actual state \( X(t) \) and the desired state \( X_d \) (\( X_d = 0 \) for civil structures).

The discrete form of the adaptation rule (Eq. (12)) is written:
\[
G(t) = G(t-1) - \Delta \gamma \nu(t)\dot{\hat{A}}_b s(t)
\]  

(14) To demonstrate the stability of the backpropagation rule, consider the following positive definite Lyapunov function \( V(t) \)
\[
V(t) = \frac{1}{2}(\dot{\nu}^T(t) + G^T(t)\Gamma^{-1}G(t))
\]  

(15) where the tilde denotes the error between the actual and desired values \( \tilde{G}(t) = G(t) - G_{\nu}(t) = \nu(t) - \nu_d(t) \) with subscripts \( \nu \) denoting the desired value. The time derivative \( \dot{V}(t) \) is given by
\[
\dot{V}(t) = s(t)^T \dot{\nu}(t) + G^T(t)\Gamma^{-1}G(t)\nu(t)
\]  

(16) Substituting Eq. (12) in Eq. (16) gives
\[
\dot{V}(t) = s(t)^T \dot{\nu}(t) + G^T(t)\Gamma^{-1}G(t)\nu(t) - (\hat{G}(t)\nu(t) + G_{\nu}(t)\nu(t))
\]  

(17) The first term in Eq. (17) is negative definite since \( A \) is negative definite for civil structures [39]. The second term can be assumed small following a proper estimation of \( \hat{B}_\alpha \). The last term can be neglected since the delay vector \( \nu(t) \) will converge to \( \nu_d \) following the MI and FNN tests \( (\nu(t) \approx 0) \). It follows that \( \dot{V}(t) < 0 \) is negative definite, guaranteeing stability.

3.3. Sequential adaptive ISDC algorithm

Fig. 6 is a diagram of the ISDC algorithm. Its sequential application is as follows:

1. Take the last \( n \) observations of the local state \( y \).
2. Determine if \( \tau \) and \( d \) require an update (every \( n \) steps); if not, jump to step 5.
3. Conduct the MI test on the last \( n \) observations to select \( \tau^* \):
   (a) Compute the probabilities \( p(\tau) \) based on the last \( n \) observations in \( y \).
   (b) Compute \( \tau^* \) (Eq. (4)).
4. Conduct the FNN test by taking the last \( n \) observations and \( \tau^* \) obtained from the MI test to determine the optimal embedding dimension \( d^* \):
   (a) Identify the false nearest neighbors and calculate the Euclidean distance \( R(t) \) with different embedding dimensions.
   (b) Select \( d^* \) that satisfies Eqs. (5) and (6).
5. Adapt \( \tau(t) \) and \( d(t) \) using Eqs. (8) and (9), respectively.
6. Construct the delay vector \( \nu(t) \).
7. Calculate the sliding surface error \( s(t) \) (Eq. (13)) and adapt \( G(t) \) using Eq. (14).
8. Compute the required control force \( u(t) = G(t)\nu(t) \).

\[\text{Fig. 5. Input-output representation of ISDC.}\]
4. Verification on SDOF

In this section, the ISDC performance is assessed on an SDOF system subjected to different types of hazard including high wind, blast and seismic events. System properties and simulation parameters are listed in Table 1. The control force $u(t)$ is generated from an ideal actuator (e.g., no delay) bounded by $u_{max}$. The maximum displacement is selected as the control objective to evaluate the performance of the controller. Different pre-defined observation sizes $n$ are selected for different types of excitation to be consistent with their durations. For example, values for $n$ under blast and seismic loads are smaller than for wind excitations. The VMDC, which is the specialized version of the ISDC with $d$ kept fixed and validated in Ref. [40], is used as a benchmark for comparison. The VMDC shares the same adaptive control rules as the ISDC, but with $d = 2$.

The numerical integration follows the discrete form of a Duhamel integral involving the free vibration response [1]

$$X(t + 1) = e^{A_h}X(t) + A^{-1}(e^{A_h}I)\{BF(t) + L_2a(t) + B_0u(t)\}$$

The methodology used for generating each hazard is described in what follows.

4.1. Wind load

A variable wind speed model is used to simulate wind speed time series $v_w(t)$ [56]:

$$v_w(t) = v_d + v_t(t) + v_g(t)$$

where $v_d$ is the design average wind speed, $v_t$ is the wind turbulence and $v_g$ is a sinusoidal wind gust:

$$v_g(t) = \begin{cases} 0 & \text{if } t < T_{sg} \\ \eta_g \sin(\omega_g t) & \text{if } T_{sg} < t < T_{eg} \\ 0 & \text{if } t > T_{eg} \end{cases}$$

where $T_{sg}$ and $T_{eg}$ are the start and end time of the wind gust, respectively, $\eta_g$ is the gust amplitude and $\omega_g$ is the gust frequency. The wind speed ramp $v_r(t)$ is modeled as:

$$v_r(t) = \begin{cases} 0 & \text{if } t < T_{sr} \\ A_{ramp} \frac{t - T_{sr}}{T_{er} - T_{sr}} & \text{if } T_{sr} < t < T_{er} \\ 0 & \text{if } t > T_{er} \end{cases}$$

where $A_{ramp}$ is the amplitude of wind speed ramp, $T_{sr}$ and $T_{er}$ are its corresponding starting and end time, respectively. The wind turbulence $v(t)$ is generated by the waves superposition formula [57,58]:

$$v(t) = \sqrt{\sum_{j=1}^{N_\omega} \left[ P_j(\omega_j) \Delta \omega \right]^2 \cos(\omega_j t + \phi_j)}$$

where $N_\omega$ is the number of equally spaced frequency points, $\Delta \omega$ is a frequency step amplitude, $\phi_j$ is a random phase uniformly distributed between 0 and $2\pi$ and $P_j(\omega_j)$ is a wind turbulence power density function [59] with a cutoff frequency $\omega_c = N_\omega \Delta \omega$:

$$P_j(\omega_j) = h_{0j} \left( \frac{h}{h_{0j}} \right)^{\lambda - 1} \left( 1 + 1.5 \frac{\omega_j}{\omega_c} \right)^{-5/3}$$

**Table 1**

<table>
<thead>
<tr>
<th>Object</th>
<th>Parameter class</th>
<th>Parameter</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
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</tr>
<tr>
<td></td>
<td>Mass</td>
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</tr>
<tr>
<td></td>
<td>Stiffness</td>
<td>$k$</td>
<td>2 kN/m</td>
</tr>
<tr>
<td></td>
<td>Damping ratio</td>
<td>$\xi$</td>
<td>2%</td>
</tr>
<tr>
<td>Input</td>
<td>Sampling rate</td>
<td>$\Delta t$</td>
<td>0.004 s</td>
</tr>
<tr>
<td></td>
<td>Maximum force</td>
<td>$u_{max}$</td>
<td>2 kN</td>
</tr>
<tr>
<td></td>
<td>Initial gain value</td>
<td>$g_0(t = 0)$</td>
<td>4 kN/m</td>
</tr>
<tr>
<td></td>
<td>Discrete bin number</td>
<td>$M_{bin}$</td>
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</tr>
<tr>
<td></td>
<td>FNN threshold</td>
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<td>FNN threshold</td>
<td>$A_{tol}$</td>
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<td>Observation size (wind)</td>
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<td>Observation size (blast)</td>
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<td></td>
<td>Observation size (earthquake)</td>
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</tr>
<tr>
<td></td>
<td>Learning rate</td>
<td>$\gamma$</td>
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<td></td>
<td>Weight</td>
<td>$\lambda$</td>
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<td></td>
<td>Weight</td>
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<td></td>
<td>Weight</td>
<td>$\eta_2$</td>
<td>$n/6$</td>
</tr>
</tbody>
</table>

Fig. 6. Block diagram of the ISDC algorithm.
where \( h \) is the height from the ground (m), \( l \) is the turbulence length scale (m) and \( h_0 \) is the roughness length in meters. The wind load \( f(t) \) is generated based on time series of wind speed \( v_w(t) \) [60]:

\[
f_w(t) = 0.5 \rho A_w C_v v_w(t) v_w(t)^{0.5} \left| v_w(t) \right|
\]

(24)

where \( \rho \) is the air density, \( A_w \) is the area exposed to the wind flow, and \( C_v \) the combined pressure coefficient, taken as 0.8 (ASCE 7-10, Fig. 27.4-1) [61].

A 10-min time series of wind speed is generated and parameter values are listed in Table 2. The wind speed gust frequency is tuned to the natural frequency \( \omega_n \) of the SDOF system and the maximum magnitude of wind load is scaled to 2 kN. The time series of wind load for the SDOF system is plotted in Fig. 7.

### 4.2. Blast load

The blast load \( f(t) \) is approximated using a general descending pulse model [62] for the positive phase and a bilinear equation [63] for the negative phase, as shown in Fig. 8. The positive phase of the blast load has the form

\[
f(t) = f_{max} \left[ 1 - \lambda_b t / \tau_d \right] e^{-\gamma_b t / \tau_d}
\]

(25)

where \( f_{max} \) is the maximum blast force, \( \tau_d \) is the blast duration, and \( \lambda_b \) and \( \gamma_b \) are constant. The negative phase is approximated by

\[
f(t) = \begin{cases} 
2f_{max} - \left( \frac{t - \tau_d}{\tau_d} \right) & \text{if } \tau_d < t < \tau_d + \tau_n/2 \\
-2f_{min} \left( \frac{t - \tau_d + \tau_n/2}{\tau_n} \right) & \text{if } \tau_d + \tau_n/2 < t < \tau_d + \tau_n 
\end{cases}
\]

(26)

Parameter values of the simulated blast load for the SDOF system are taken from the 1995 Oklahoma City Bombing event [64] and listed in Table 3. Analogous to the wind load, the maximum blast load \( f_{max} \) is scaled to 2 kN.

### 4.3. Seismic load

The earthquake input is taken as the North-South component of the 1940 El Centro earthquake and resampled to match the sampling rate of 250 Hz in the simulation, as shown in Fig. 9.

### 4.4. Simulation results

A performance index \( J \) that describes the maximum displacement reduction in the SDOF system is used to quantify performance:

\[
J = \frac{\max[|y_{unc}(t)|] - \max[|y(t)|]}{\max[|y_{unc}(t)|]}
\]

(27)

where \( y(t) = x(t) \) is the controlled displacement, and \( y_{unc}(t) \) is the uncontrolled displacement.

Values of performance index \( J \) for the ISDC and VMDC strategies...
under multi-hazard excitations are listed in Table 4. Results demonstrate that the ISDC outperforms the VMDC, except for the case of the blast excitation. The time series of displacement responses and evolutions of τ and d are plotted in Figs. 10–12. Fig. 10(a) shows the first 60 s (typical) of the displacement response under wind excitation. A study of Fig. 10(b) shows that the improvement in performance for the ISDC arose from the evolution of ISDC parameters, as the embedding for the VMDC is held constant at d = 2. The performance of both controllers is identical for the blast load (Fig. 11) because the embedding dimension of the ISDC remained constant under free vibration and yielded an identical input space. The performance of the ISDC under the seismic event (Fig. 12(a)) resembles that of the wind event, where the performance improved relative to the VMDC due to the adaptation of the input space dimension. It can be observed in Fig. 12(b) that the time delay τ converges to 0.2 s after the seismic excitation (12 s). In this introductory multi-hazard mitigation example, the SDOF system coupled with an ideal actuator is relatively simple, which results in d remaining constant for almost the complete duration of the events. This should not be expected in an MDOF system equipped with nonlinear control devices.

### 5. Simulations on full-scale structures

Two benchmark buildings are selected as numerical examples for structural control applications. Each structure is equipped with a semi-active friction device previously proposed by the authors, termed Modified Friction Device (MFD). Previous simulations conducted on these two structures consisted of demonstrating the mitigation potential of the MFD controlled using a sliding mode controller (SMC) [65]. Here, the MFD is controlled with the ISDC and simulated under non-simultaneous multi-hazard loads. Results of the ISDC are also compared with the ones obtained under the SMC. This discussion is followed by an assessment of performance under various uncertainties to study the ISDC’s robustness to dynamic parameters.

#### 5.1. Simulated structures

Two benchmark structures are selected including a short building and a tall building. The short building is a five storey steel structure located in Shizuoka City, Japan and the tall building is a 39 story office tower located in Boston, MA. The weak direction of both structures were modeled in Ref. [65]. Their model periods and effective modal mass are listed in Table 5. The MFD is installed at every floor in the short building, and at every other floor in the tall building. The design of its damping capacity $u_{l,\text{max}}$ was conducted following a motion-based design methodology [65]. The corresponding values are listed in Tables 6 and 7.

The equation of motion in a n-story building has the form:

$$\mathbf{M} \ddot{\mathbf{x}} + \mathbf{C} \dot{\mathbf{x}} + \mathbf{K} \mathbf{x} = -
\mathbf{M} \mathbf{E}_f \mathbf{q}_d + \mathbf{E}_f \mathbf{F} + \mathbf{E}_u \mathbf{u} \quad (28)$$

where $\mathbf{x} \in \mathbb{R}^{nx1}$ is the displacement vector, $\mathbf{a}_d$ is the seismic acceleration, $\mathbf{F} \in \mathbb{R}^{nx1}$ is the external loading input vector, $\mathbf{u} \in \mathbb{R}^{nx1}$ is the control input vector, $\mathbf{M} \in \mathbb{R}^{nxn}$, $\mathbf{C} \in \mathbb{R}^{nxn}$, $\mathbf{K} \in \mathbb{R}^{nxn}$ are the mass, damping, and stiffness matrices, respectively; and $\mathbf{E}_f \in \mathbb{R}^{nxn}$, $\mathbf{E}_g \in \mathbb{R}^{nxn}$, and $\mathbf{E}_u \in \mathbb{R}^{nx1}$ are the seismic acceleration, external loading, and control input location matrices, respectively.

Numerical integration (Eq. (18)) uses the state-space representation of Eq. (28) that is given by

$$\dot{\mathbf{X}} = \mathbf{A} \mathbf{X} + \mathbf{B}_g \mathbf{F} + \mathbf{B}_u \mathbf{u} + \mathbf{B}_d \mathbf{a}_d \quad (29)$$

where $\mathbf{X} = [\mathbf{x} \ \dot{\mathbf{x}}]^T \in \mathbb{R}^{2nx1}$ is the state vector with various constant coefficient matrices defined as follows:

$$\mathbf{A} = \begin{bmatrix} 0 & \mathbf{I} \\ -\mathbf{M}^{-1} \mathbf{K} & -\mathbf{M}^{-1} \mathbf{C} \end{bmatrix}_{2nx2n} \quad \mathbf{B}_g = \begin{bmatrix} \mathbf{0} \\ -\mathbf{M}^{-1} \mathbf{E}_f \end{bmatrix}_{2nx1} \quad \mathbf{B}_u = \begin{bmatrix} \mathbf{0} \\ -\mathbf{M}^{-1} \mathbf{E}_u \end{bmatrix}_{2nx1} \quad \mathbf{B}_d = \begin{bmatrix} \mathbf{0} \\ -\mathbf{E}_g \end{bmatrix}_{2nx1}$$

#### 5.2. Semi-active control device

The mechanical principle of the MFD is based on duo-servo drum brake technology and the damping force $u$ is obtained by varying the actuation pressure $W$. Fig. 13 shows the dynamic behavior of a 3.1 kN MFD under a harmonic excitation of amplitude 2.54 cm at 0.5 Hz in terms of % damping capacity. Its dynamic is modeled using a 3-stage dynamic model [66]. Stage 1 is a typical friction dynamic and the damping force $u$ is modeled using a LuGre friction model:

![Fig. 10. SDOF subjected to wind excitation: (a) first 60 s of the displacement response; and (b) evolution of the time delay $\tau$ and embedding dimension $d$ for the ISDC.](image-url)
where $\sigma_0$ represents the aggregate bristle stiffness, $\sigma_1$ microdamping, $\sigma_2$ viscous friction, $\zeta$ an evolutionary variable, $z$ and $\dot{z}$ the device displacement and velocity, and $g(z)$ a function that describes the Stribeck effect in which $\zeta_s$ is a constant modeling the Stribeck velocity, $F_s$ the static frictional force, and $F_k$ the kinetic frictional force. Values of model parameters $\sigma_0, F_s$, and $F_k$ are linearly dependent on the actuation pressure $W$.

Fig. 11. SDOF subjected to blast excitation: (a) displacement response; and (b) evolution of the time delay $\tau$ and embedding dimension $d$ for the ISDC.

Fig. 12. SDOF subjected to seismic excitation: (a) displacement response; and (b) evolution of the time delay $\tau$ and embedding dimension $d$ for the ISDC.

### Table 5
Fundamental periods of simulated buildings.

<table>
<thead>
<tr>
<th>Mode</th>
<th>Short building</th>
<th>Tall building</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Natural period (s)</td>
<td>Effective mass (%)</td>
</tr>
<tr>
<td>First</td>
<td>0.991</td>
<td>82.81</td>
</tr>
<tr>
<td>Second</td>
<td>0.354</td>
<td>11.15</td>
</tr>
<tr>
<td>Third</td>
<td>0.223</td>
<td>3.68</td>
</tr>
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</table>

### Table 6
Damper configuration for short building.

<table>
<thead>
<tr>
<th>Floor</th>
<th>$u_{\text{max}}$ (kN)</th>
<th># devices</th>
</tr>
</thead>
<tbody>
<tr>
<td>5</td>
<td>263</td>
<td>2</td>
</tr>
<tr>
<td>4</td>
<td>280</td>
<td>2</td>
</tr>
<tr>
<td>3</td>
<td>310</td>
<td>2</td>
</tr>
<tr>
<td>2</td>
<td>353</td>
<td>2</td>
</tr>
<tr>
<td>1</td>
<td>461</td>
<td>2</td>
</tr>
</tbody>
</table>

### Table 7
Damper configuration for tall building.

<table>
<thead>
<tr>
<th>Floor</th>
<th>$u_{\text{max}}$ (kN)</th>
<th># devices</th>
</tr>
</thead>
<tbody>
<tr>
<td>Above 26th floor</td>
<td>135</td>
<td>8</td>
</tr>
<tr>
<td>Below 26th floor</td>
<td>270</td>
<td>22</td>
</tr>
</tbody>
</table>

$$u = \sigma_0 \zeta + \sigma_1 \dot{z} + \sigma_2 \zeta$$
$$\dot{\zeta} = z - \sigma_0 \frac{u}{W}$$
$$g(z) = F_s + (F_k - F_s)e^{-\zeta_s^2}$$

(30)
\( F_1 = C_1 W \)
\( F_2 = C_2 W \)
\( \sigma_0 = \alpha_0 W + \sigma_0 |v_{w\text{--}0} \)  
(31)

where \( C_i, C_2, \sigma_0 \), and \( \sigma_0 |v_{w\text{--}0} \) are constants. Stage 2 and 3 are two linear stiffness regions that represent the backlash effect in the MFD. The damping force \( u \) is modeled as linear stiffness elements \( k_2 \) and \( k_3 \) during displacements \( d_2 \) and \( d_3 \) in stage 2 and 3, respectively. Additionally, a smooth transition region between three distinct stages is generated using a \( C^m \) function [28]:

\[
\psi(z) = \frac{1}{1 + e^{-\frac{z}{\gamma_1(z)}}} \psi_1 + \frac{1}{1 + e^{-\frac{z}{\gamma_2(z)}}} \psi_2 
\]
(32)

where \( z_0 \) is the reference displacement of the new stage, and \( \gamma_1 \) and \( \gamma_2 \) are constants. The damping force \( u \) within the transition from stage \( i \) to stage \( j \) is written as:

\[
u = (1-\psi(z))u_i + \psi(z)u_j
\]
(33)

The model parameter values used in the simulation are listed in Table 8. The damping capacity of the MFD in the simulation is scaled to the design capacity \( u_{i\text{--}max} \) by selecting corresponding actuation pressure \( W \) such that \( F_2 = u_{j\text{--}max} = C_j W \).

5.3 Multi-hazard excitations

Non-simultaneous multi-hazards are generated for each structure including wind, blast, and seismic loads. Two time series of wind loads are simulated based on Eq. (24) for each structure, with a wind speed gust frequency acting on the first (wind1) and second (wind2) natural frequencies. The time series wind speed \( v_{w,j}(t) \) is distributed on each floor following a power law

\[
v_{w,j}(t) = v_{w\text{--}top}(t) \left( \frac{h_j}{h_{\text{top}}} \right)^p
\]
(34)

where \( v_{w\text{--}top} \) is the wind speed series at the top floor, \( v_{w,j}(t) \) is the wind speed at floor \( i \) of height \( h_i \) and \( p \) is a constant taken as 0.143 [67]. Parameter values used in generating the wind loads at the top floor of each building are listed in Table 9.

The Oklahoma bombing event of 1995 is used with parameter values listed in Table 3 except for \( f_{\text{max}} \) and \( f_{\text{min}} \). The peak positive and negative blast load \( f_{\text{max}} \) and \( f_{\text{min}} \) at each floor are determined follows the example provided in Ref. [64] and listed in Table 10. Note that only the first seven floors in the tall building are assumed to be affected by the blast.

Six different earthquakes are selected including three near-field and three far-field earthquakes defined based on their epicentral distance, with 0–50 km for near-field and beyond 50 km for far-field. The seismic input is scaled based on the local design response spectra of each building. Simulated earthquakes and their corresponding scale factor are listed in Table 11. Details on the scaling methodology can be found in Ref. [65].

5.4 Control cases

Eight different control cases are investigated including five sliding mode control (SMC) cases, the VMDC, the ISDC, and the passive-on
Table 10  
Peak blast load $f_{\text{max}}$ and $f_{\text{min}}$ for simulated buildings.

<table>
<thead>
<tr>
<th>Floor number</th>
<th>Height (m)</th>
<th>Short building</th>
<th>Tall building</th>
<th>Height (m)</th>
<th>Short building</th>
<th>Tall building</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>4.2</td>
<td>413,280</td>
<td>1008</td>
<td>4.57</td>
<td>533,100</td>
<td>1300</td>
</tr>
<tr>
<td>2</td>
<td>7.8</td>
<td>138,240</td>
<td>337</td>
<td>12.2</td>
<td>234,040</td>
<td>570</td>
</tr>
<tr>
<td>3</td>
<td>11.4</td>
<td>43,200</td>
<td>105</td>
<td>18.3</td>
<td>53,635</td>
<td>130</td>
</tr>
<tr>
<td>4</td>
<td>15</td>
<td>6307</td>
<td>15</td>
<td>22.2</td>
<td>6170</td>
<td>15</td>
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<td>18.6</td>
<td>2073</td>
<td>5</td>
<td>26.2</td>
<td>2028</td>
<td>5</td>
</tr>
<tr>
<td>6</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>30.2</td>
<td>929</td>
<td>2</td>
</tr>
<tr>
<td>7</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>34.1</td>
<td>676</td>
<td>1</td>
</tr>
</tbody>
</table>

(i.e., constant full power) case. The ISDC and VMDC utilize local states including interstory displacement and velocity at the device location and each MFD is controlled decentrally. The ISDC parameters used in the simulation are listed in Table 12. Observation size $n$ is also adjusted based on the duration of the events.

The SMC assumes full state knowledge of the building system (e.g., mass, damping, and stiffness) and states (e.g., interstory displacements and velocities). The required control force from the SMC takes form (35):

$$u_{\text{req}, \text{SMC}} = -\mu\{\Theta B_a^T[\Theta B_a]\}^{-1}[\Theta B_a]^T S$$

where $\Theta = [\Theta | I] \in \mathbb{R}^{n \times 2n}$ is a positive definite weight matrix with positive constant $\theta$ and $S = \Theta (X - X_0)$ is a sliding surface with the desired state $X_0$. Five sliding mode control cases (SMC1–SMC5) with different sets of parameter values $\theta$ and $\mu$ are used and listed in Table 13. These parameters were pre-tuned to optimize the performance for each building under different excitations.

The MFD is controlled through the variation of a voltage that follows the dynamics

$$v_{\text{act}} = -v_{\text{delay}}(v_{\text{act}} - v_{\text{req}})$$

where $v_{\text{act}}$ is the actual voltage, $v_{\text{req}}$ is the required voltage following a required control force, and $v_{\text{delay}}$ is a positive constant taken as $200 \text{ s}^{-1}$ based on previous simulations conducted in [68].

5.5. Performance indices

Two performance indices are used to evaluate the performance of different control cases:

- Maximum interstory drift reduction $J_1$

$$J_1 = \frac{\max_i \{\dot{x}_{\text{ctrl}}(t)\} - \max_i \{\dot{x}_{\text{unc}}(t)\}}{\max_i \{\dot{x}_{\text{unc}}(t)\}}$$

where $\dot{x}_i = x_i - x_{i-1}$ is the controlled interstory displacement at floor $i$, and $\dot{x}_{\text{unc}}$ is the uncontrolled interstory displacement.

- Maximum absolute acceleration reduction $J_2$

Table 11  
List of simulated earthquakes.

<table>
<thead>
<tr>
<th>Location</th>
<th>Year</th>
<th>Station</th>
<th>Dist (km)</th>
<th>Scale factor</th>
</tr>
</thead>
<tbody>
<tr>
<td>Near-field</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Kobe, Japan</td>
<td>1995</td>
<td>Nishi-Akashi</td>
<td>7.1</td>
<td>2.91</td>
</tr>
<tr>
<td>San Francisco, CA</td>
<td>1957</td>
<td>Golden Gate Park</td>
<td>9.6</td>
<td>65.72</td>
</tr>
<tr>
<td>Imperial Valley, CA</td>
<td>1940</td>
<td>El Centro Array 9</td>
<td>13</td>
<td>1.93</td>
</tr>
<tr>
<td>Far-field</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Loma Prieta, CA</td>
<td>1989</td>
<td>Oakland Title</td>
<td>72.1</td>
<td>2.48</td>
</tr>
<tr>
<td>Chi-Chi, Taiwan</td>
<td>1999</td>
<td>CHY012</td>
<td>59</td>
<td>8.41</td>
</tr>
<tr>
<td>Big Bear City, CA</td>
<td>2003</td>
<td>Caltech Millikan Library</td>
<td>118</td>
<td>45.30</td>
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Table 12  
ISDC parameters for building simulation.

<table>
<thead>
<tr>
<th>Object</th>
<th>Parameter class</th>
<th>Parameter</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Short building</td>
<td>Tall building</td>
<td>Short building</td>
<td>Tall building</td>
</tr>
<tr>
<td>Input</td>
<td>Initial gain value</td>
<td>$g_1(t = 0)$</td>
<td>200 kN/m</td>
</tr>
<tr>
<td></td>
<td>Initial gain value</td>
<td>$g_2(t = 0)$</td>
<td>$-100$ kN/m $\times 10^6$ kN/m</td>
</tr>
<tr>
<td></td>
<td>Initial embedding dimension</td>
<td>$d(t = 0)$</td>
<td>2</td>
</tr>
<tr>
<td></td>
<td>Initial time delay</td>
<td>$\tau(t = 0)$</td>
<td>0 s</td>
</tr>
<tr>
<td></td>
<td>Sampling rate</td>
<td>$\Delta_t$</td>
<td>0.004 s</td>
</tr>
<tr>
<td></td>
<td>Discrete bin number</td>
<td>$M_{bin}$</td>
<td>30</td>
</tr>
</tbody>
</table>

Table 13  
Sliding mode control cases.

<table>
<thead>
<tr>
<th>Simulation case</th>
<th>Short building</th>
<th>Tall building</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\theta$</td>
<td>$\mu$</td>
<td>$\Theta$</td>
</tr>
<tr>
<td>SMC1</td>
<td>1</td>
<td>50</td>
</tr>
<tr>
<td>SMC2</td>
<td>1</td>
<td>100</td>
</tr>
<tr>
<td>SMC3</td>
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<td>100</td>
</tr>
<tr>
<td>SMC4</td>
<td>10</td>
<td>150</td>
</tr>
<tr>
<td>SMC5</td>
<td>100</td>
<td>150</td>
</tr>
</tbody>
</table>

where $\dot{x}_i$ is the controlled acceleration and $\dot{x}_{\text{unc}}$ is the uncontrolled acceleration.

5.6. Simulation results – short building

The performance indices $J_1$ and $J_2$ for the short building are shown in Fig. 14. The figure only shows the best and worst results among all SMC cases for each hazard, with the range marked by the black line. The comparison of the overall mitigation performances shows that the ISDC significantly outperforms the passive-on case for both $J_1$ and $J_2$. This is expected given the added reachability by varying the control input. The VMDC (ISDC with $d = 2$) performs better than the passive-on case in most cases except for $J_2$ under hazard EQ5. A comparison between ISDC and VMDC shows that the ISDC outperforms the VMDC in most cases except for $J_2$ under hazard wind2, consistent with results.
obtained in the SDOF simulations, showing that varying the embedding dimension has a positive impact on mitigation performance.

A comparison of the ISDC and SMC cases shows that the ISDC provides better performance results than most of the SMC cases except for $J_1$ under hazard EQ6. The SMC performs better overall under the wind and blast loads. Nevertheless, the performance of the ISDC is achieved with local states only, and without varying any of the ISDC control parameters, except for the observation size $n$. Conversely, the best performance from the SMC depends on parameters tuned to the hazard types, and is based on full state knowledge. For example, SMC1 provides the best $J_2$ performance under wind2, yet the worst $J_2$ performance among SMC cases under wind2 (and underperforming the ISDC).

Fig. 15 plots the evolution of the ISDC parameters $\tau$ and $d$ under wind1 (first 60 s), blast (first 1 s), and seismic (EQ1) loads taken at the 3rd floor which corresponds to the location of the largest displacement under wind and seismic loads. It can be observed that $d$ varied between 2 and 3 for both the wind and earthquake excitations. The embedding remained constant at $d = 2$ under blast load, because the system entered a free-vibration mode immediately after the blast impulse.

5.7. Simulation results – tall building

Performance indices $J_1$ and $J_2$ for the tall building are plotted in Fig. 16. Similar to the short building, the ISDC outperforms passive-on case (except for $J_2$ under hazard EQ5). A comparison between ISDC and VMDC shows that the ISDC underperforms the VMDC only under some hazards in performance index $J_1$, including hazards EQ2, EQ5 and EQ6. In the case of wind and blast excitations, the ISDC and VMDC perform similarly, except for J2-wind1, where the ISDC outperforms the VMDC. The ISDC underperforms the best SMC cases under most hazards (except J1-EQ1,2,6 and J2-EQ1). Nevertheless, the SMC cases exhibit large variations in performance, varying up to 50% under J1-EQ4 and J2-EQ4. More importantly, while the SMC cases achieve the best performance for the majority of the hazards, mistuning may lead to worsened performance with respect to the uncontrolled cases (i.e., negative performance indices), while the ISDC consistently provides energy dissipation.

Fig. 17 plots the evolution of the ISDC parameters $\tau$ and $d$ under wind (first 60 s), blast (first 1 s) and seismic (EQ1) loads at the 33th floor, which corresponds to the location of the largest acceleration. Dissimilar to the short building, the embedding dimension remains constant at $d = 2$ under both the wind and blast loads given the nearly periodic response of the 33th floor, where the tall structure acts similarly to a low-pass filter, resulting in ISDC and VMDC performances being similar. However, a higher $d$ value is reached under Kobe earthquake due to the higher complexity in the response. The $\tau$ value remains small in the case of blast loads due to the small observation size, as observed in the short building simulation.

5.8. Robustness to uncertainty

Simulation results have shown that the ISDC is robust with respect to different hazards, while the SMC cases were dependent on hazard-specific parameters to achieve an optimal performance. Here, we investigate the robustness of the ISDC with respect to dynamic parameters. The robustness with respect to sensor failure is not investigated, because in the studied architecture the controller relies on a single sensor, and one would need to address such robustness through designing the control system with appropriate redundancy. An error on the estimated mass of the structure is introduced in the controlled models, and the mitigation performances compared. Such estimation error leads to an estimation error in $B$, used in the ISDC adaptive control gain rule (Eq. (12)) and the SMC required force (Eq. (35)). A range of ±20% in mass is considered, generated by multiplying each floor mass by 1.2 and 0.8 (i.e., only considering the extreme cases). Figs. 18 and 19 plot the performance indices for both simulated buildings under all hazards. The uncertainty performance ranges of the ISDC and all SMCs are shown by the red and black solid lines, respectively. The red star and green square mark the ISDC and best-case SMC results, respectively, previously obtained from the exact mass.

Results show that the ISDC’s performance indices vary less than 10% except for $J_1$-EQ3-short building. Conversely, SMCs provide a wide range of variability. Of particular interest is the case of the tall building, where uncertainty led to a 60% variation of performance for the SMC and only 2% variation in performance for the ISDC. It follows that the ISDC offers more robustness with respect to uncertain dynamic parameters.

6. Conclusion

This paper introduced a novel time delay feedback controller, termed Input Space Dependent Controller (ISDC). The ISDC is a sequential adaptive data-driven controller, tailored to the challenge of semi-active control of structures subjected to multi-hazard. The particularity of the ISDC is the utilization of a time-varying input-space, which allows the representation to adapt quickly to different excitation dynamics. Here, the varying input space was combined with an
adaptive time delay representation to construct the controller. The strategy consists of sequentially selecting the controller’s optimal time delay and embedding dimension, and adjusting the representation accordingly.

The ISDC was first verified on a single degree-of-freedom (SDOF) system by comparing its performance to a previously investigated, 

![Fig. 15. Evolution of τ and d for the 3rd floor – ISDC case, short building: (a) wind1 (first 60 s); (b) blast (first 1 s); and (c) EQ1.](image1)

![Fig. 16. Performance of controlled tall building under multi-hazard excitation: (a) J1; and (b) J2.](image2)
Fig. 17. Evolution of $\tau$ and $d$ for the 33rd floor – ISDC case, tall building: (a) wind1 (first 60 s); (b) blast (first 1 s); and (c) EQ1.

Fig. 18. Uncertainty in mass – short building: (a) $J_1$; and (b) $J_2$. 
specialized form where an embedding dimension of two is selected and remains constant, termed Variable Multi-Delay Controller (VMDC). The SDOF was subjected to non-simultaneous wind, blast, and seismic loads. Results show that the ISDC outperformed the VMDC by enabling a variation in the embedding dimension, yet performed similarly when the system responded periodically.

The ISDC was then validated on two realistic full-scale structures, one short and one tall, equipped with a variable friction device, termed the Modified Friction Device (MFD), subjected to a series of non-simultaneous hazards consisting of two wind loads, one blast load, and six earthquake loads. Simulations compared the performance of the ISDC to the VMDC, five sliding mode controllers (SMC), and one passive-on controller. Overall, the ISDC performed better than the VMDC, as expected from the simulations on the SDOF. It also performed better than the passive-on case given the higher control reachability. It was capable of achieving better or similar mitigation performance compared with the best of five SMC cases in the short building. For the tall building, while the ISDC underperformed the best SMC cases for most of the excitations, the SMCs exhibited high variation in performance and often led to worsening of vibrations with respect to the uncontrolled case, demonstrating a lack of robustness with respect to mistuning.

The performance of the ISDC was achieved with local states only, and without varying any of its control parameters, except for the observation size $n$, while the best performance from the SMC depended on hazard-specific pre-tuned control parameters and was based on full state knowledge. A last set of simulations on the full-scale structures was conducted to evaluate the robustness of the ISDC to uncertainties in dynamic parameters, in particular a change in mass. Results show that the ISDC was very robust, yielding approximately no more than 10% variation in performance over a 20% variation in mass (except for one specific case), while SMCs yielded very high variations, reaching up to 60% changes in performances. Overall, the ISDC provided consistent better performance than most other controllers described in this paper.

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