Control of Large-Scale Structures
with Large Uncertainties

by

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Abstract

Performance-based design is a design approach that satisfies motion constraints as its primary goal, and then verifies for strength. The approach is traditionally executed by appropriately sizing stiffnesses, but recently, passive energy dissipation systems have gained popularity. Semi-active and active energy dissipation systems have been shown to outperform purely passive systems, but they are not yet widely accepted in the construction and structural engineering fields. Several factors are impeding the application of semi-active and active damping systems, such as large modeling uncertainties that are inherent to large-scale structures, limited state measurements, lack of mechanically reliable control devices, large power requirements, and the need for robust controllers.

In order to enhance acceptability of feedback control systems to civil structures, an integrated control strategy designed for large-scale structures with large parametric uncertainties is proposed. The control strategy comprises a novel controller, as well as a new semi-active mechanical damping device.

Specifically, the controller is an adaptive black-box representation that creates and optimizes control laws sequentially during an excitation, with no prior training. The novel feature is its online organization of the input space. The representation only requires limited observations for constructing an efficient representation, which allows control of unknown systems with limited state measurements.

The semi-active mechanical device consists of a friction device inspired by a vehicle drum brakes, with a viscous and a stiffness element installed in parallel. Its unique characteristic is its theoretical damping force reaching the order of 100 kN, using a friction mechanism powered with a single 12-volts battery. It is conceived using mechanically reliable technologies, which is a solution to large power requirement and mechanical robustness.

The integrated control system is simulated on an existing structure located in Boston, MA, as a replacement to the existing viscous damping system. Simulation results show that the integrated control system can mitigate wind vibrations as well as the current damping strategy, utilizing only one third of devices. In addition, the system created effective control rules for several types of earthquake excitations with no prior training, performing similarly to an optimal controller using full parametric and state knowledge.

Thesis Supervisor: Jerome J. Connor
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Contents

List of Figures 13

List of Tables 23

1 Introduction 27
   1.1 Why Feedback Control for Civil Structures? ............. 28
   1.2 Control of Uncertain Systems: The Civil Engineering Challenge 30
      1.2.1 Model Uncertainties .......................... 31
      1.2.2 Sensors and Observers ......................... 32
      1.2.3 Actuators ..................................... 32
      1.2.4 Controllers ................................. 33
   1.3 Problem Statement ................................ 36
      1.3.1 Numerical Example ............................ 38
   1.4 Proposed Control System & Contributions ............... 42
   1.5 Benchmark Problems and Simulations .................... 43
   1.6 Notes on Terminology ............................. 45
   1.7 Organization of the Dissertation ....................... 46

2 Control Algorithms for Large Parametric Uncertainties 49
   2.1 Introduction ...................................... 51
      2.1.1 Transfer Function Models ..................... 51
   2.2 Fixed Controllers ................................. 56
      2.2.1 $H_\infty$-Based Controllers .................. 56
      2.2.2 Linear Quadratic-Based Controllers .......... 57
      2.2.3 Lyapunov-Based Controllers .................. 60
   2.3 Adaptive Controllers .............................. 64
      2.3.1 MRAC & STC .................................. 65
      2.3.2 Intelligent Controllers ...................... 70
   2.4 WNN for Semi-Active Control ......................... 74
      2.4.1 Network Architecture .......................... 75
      2.4.2 Wavelet Functions ............................ 77
      2.4.3 Self-Organizing Mapping ...................... 80
      2.4.4 Self-Adapting Feature ....................... 83
      2.4.5 Discussion on Inputs, Time Delay, and Measurement Errors ......................... 88
      2.4.6 Discussion on the Control Objectives .......... 89
## CONTENTS

2.5 Conclusion ........................................... 90

3 Organizing the Input Space .......................... 91
3.1 Introduction ......................................... 93
3.2 Nonlinear Time Series Analysis ......................... 96
  3.2.1 Algebraic Topology .............................. 96
  3.2.2 Lyapunov Exponents ............................ 98
  3.2.3 Recurrence Quantification Analysis ................. 100
  3.2.4 Stationarity Index ............................ 102
3.3 Input Selection ........................................ 103
  3.3.1 Dimensionality Reduction Techniques ............... 104
  3.3.2 Embedding Theorem ............................. 108
3.4 Self-Organizing Algorithm .......................... 121
  3.4.1 Nonstationarity .................................. 123
  3.4.2 Sequential Construction of the Delayed Vector .... 125
  3.4.3 Extension to MIMO systems ....................... 126
3.5 SOI-WNN Algorithm .................................. 127
3.6 Simulations ........................................... 129
  3.6.1 Tracking of a Function .......................... 130
  3.6.2 Regularization of a 3 DOF System ................ 134
  3.6.3 Analysis of a Chaotic Excitation ................. 136
  3.6.4 Neuroprediction .................................. 142
3.7 Conclusion ........................................... 144

4 Control Devices for Large-Scale Structures ............ 145
4.1 Introduction ........................................... 146
4.2 Semi-Active Systems .................................. 149
  4.2.1 Variable Orifices ............................... 149
  4.2.2 Controllable Fluids .............................. 151
  4.2.3 Variable Stiffnesses ............................. 153
  4.2.4 Variable Frictions .............................. 154
4.3 Hybrid Systems ....................................... 156
4.4 Modified Friction Device .............................. 161
  4.4.1 Device Dynamics .................................. 163
  4.4.2 Friction Mechanism .............................. 167
  4.4.3 Brake Actuator Control ......................... 174
4.5 Conclusion ........................................... 176
## Contents

5 Simulations on Existing Structure

5.1 Introduction ................................................. 180

5.2 Simulated Structure ........................................... 181
  5.2.1 Dynamic Loads ....................................... 185
  5.2.2 Performance Indices .................................. 186

5.3 MFD performance ............................................. 188
  5.3.1 Simulation 1 ........................................... 189
  5.3.2 Simulation 2 ........................................... 191
  5.3.3 Simulation 3 ........................................... 191
  5.3.4 Simulation 4 ........................................... 193

5.4 SOI-WNN - Parameters Sensitivity ......................... 195
  5.4.1 Inputs ................................................. 196
  5.4.2 Hidden Layer ......................................... 197
  5.4.3 Outputs ............................................... 200
  5.4.4 Training .............................................. 201
  5.4.5 Global Performance .................................... 205

5.5 SOI-WNN - Wind Excitation ................................. 205
  5.5.1 Revisiting Simulation 1 ............................... 206
  5.5.2 Revisiting Simulation 2 ............................... 206
  5.5.3 Revisiting Simulation 3 ............................... 208

5.6 SOI-WNN - Earthquake Excitations ....................... 208
  5.6.1 Revisiting Simulation 4 ............................... 208
  5.6.2 All Earthquakes ...................................... 215

5.7 SOI-WNN-Augmented LQR Controller ..................... 224
  5.7.1 Wind Excitation ...................................... 226
  5.7.2 Earthquake Mitigation ............................... 226

5.8 Conclusion .................................................. 228

6 Discussion on Results and Impacts ............................. 229

6.1 Introduction ................................................ 230

6.2 Mechanical Damping Devices ............................... 230

6.3 Intelligent Control ......................................... 231
  6.3.1 Controller Parameters ................................ 233
  6.3.2 Closed-Loop System Performance ..................... 235
  6.3.3 Earthquake Excitation ................................ 236
  6.3.4 SOI-WNN-Augmented LQR Controller .................. 237

6.4 Effective Structural Systems ............................... 237

6.5 Conclusion ................................................. 239
## CONTENTS

### 7 Conclusion

7.1 Summary of Contributions & Impacts .......................... 242
  7.1.1 Modified Friction Device .............................. 242
  7.1.2 Intelligent Controller ................................. 243
  7.1.3 Integrated Control System ............................. 244

7.2 Limitations and Future Work ................................. 244
  7.2.1 Modified friction device .............................. 244
  7.2.2 Intelligent Controller ................................. 245
  7.2.3 Integrated Control System ............................. 246

### A Supplemental Earthquake Simulation Results 247

A.1 Big Bear City 2003 ........................................... 249
A.2 Chi-Chi 1999 ................................................ 250
A.3 Coalinga 1983 ................................................. 251
A.4 Coyote Lake 1979 ........................................... 252
A.5 Denali 2002 ................................................ 253
A.6 Dinar 1985 .................................................. 254
A.7 Duzce 1999 .................................................. 255
A.8 Erzican 1992 ............................................... 256
A.9 Friuli 1976 ................................................. 257
A.10 Gilroy 2002 ................................................ 258
A.11 Imperial Valley 1940 ...................................... 259
A.12 Irpinia 1980 ................................................ 260
A.13 Kern County 1952 .......................................... 261
A.14 Kobe 1995 .................................................. 262
A.15 Kocaeli 1999 ................................................ 263
A.16 Loma Prieta 1989 .......................................... 264
A.17 Mammoth Lakes 1980 ...................................... 265
A.18 Manjil 1990 ................................................ 266
A.19 Michoacan 1985 ........................................... 267
A.20 Nahanni 1985 ................................................. 268
A.21 New Zealand 1987 .......................................... 269
A.22 Norcia 1979 ................................................ 270
A.23 Northridge 1994 ............................................ 271
A.24 Parkfield 1966 .............................................. 272
A.25 San Fernando 1971 ........................................ 273
A.26 San Francisco 1957 ......................................... 274
A.27 San Salvador 1986 .......................................... 275
CONTENTS

A.28 Spitak 1988 ......................................................... 276
A.29 Tabas 1978 ......................................................... 277
A.30 Victoria 1980 ....................................................... 278

Bibliography .......................................................... 279
List of Figures

1.1 Cable displacement in function of devices location [80]. . . . . 29
1.2 Typical closed-loop control system. . . . . . . . . . . . . . . . 31
1.3 Classification of diverse control techniques in function of para-
metric uncertainties and uncertainty robustness. . . . . . . . . . 38
1.3 Mitigation results: a) Maximum displacement (cm); and b)
maximum acceleration (cm/s²). . . . . . . . . . . . . . . . . . . . 41
1.4 Organization of the theoretical chapters. . . . . . . . . . . . . 47
2.1 Stability under perturbation (adapted from [94]). . . . . . . . 57
2.2 Stability and robustness, H∞ controller. . . . . . . . . . . . . 58
2.3 Stability and robustness, LQR controller. . . . . . . . . . . . . 59
2.4 Illustration of Lyapunov stability: a) stable system; b) marginally
stable system; and c) unstable system. . . . . . . . . . . . . . . . 61
2.5 Graphical representation of SMC for n = 2 (adapted from [171]). 63
2.6 Graphical representation of chattering (adapted from [171]). . 64
2.7 Schematic representation of a) MRAC; and b) STC. . . . . . . . 66
2.8 Convergence of the estimated parameters: a) the mass ˆm; b)
the damping ˆc; and c) the stiffness ˆk. . . . . . . . . . . . . . . . . 69
2.9 Example of a fuzzy set. VS = very small; S = small; M =
moderate; L = large; VL = very large. . . . . . . . . . . . . . . . 71
2.10 Simplified schematic of a human neuron. . . . . . . . . . . . . 72
2.11 An artificial neuron (adapted from [160]). . . . . . . . . . . . . 72
2.12 ARMAX model structure of the WNN. . . . . . . . . . . . . . 76
2.13 Illustration of controlled regions C, C_t, and C_d for a 1 kN
magnetorheological damper. . . . . . . . . . . . . . . . . . . . . 78
2.14 Block diagram of the closed-loop control system. . . . . . . . . 78
2.15 2-dimensional Mexican Hat wavelet. a) Original wavelet; b)
bandwidth of the wavelet scaled up by a factor of 2; and c)
translated wavelet. . . . . . . . . . . . . . . . . . . . . . . . . . . . 80
2.16 Illustration of a wavelet neural network. . . . . . . . . . . . . 81
3.1 Illustration of the input space selection: a) function in an \(\mathbb{R}^2\)
space; and b) function in an \(\mathbb{R}^3\) space. . . . . . . . . . . . . 95
3.2 Illustration of the concept of topology a) a torus is not equiva-
lent to a sphere; and b) a coffee mug is equivalent to a donut
[2]. . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . 96
<table>
<thead>
<tr>
<th>Figure</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>3.3</td>
<td>a) An embedding map $\phi$ of the smooth manifold $\mathcal{M}$ into $\mathbb{R}^2$; b) an immersion that is not a one-to-one; and c) and one-to-one that is not an immersion (adapted from [162]).</td>
</tr>
<tr>
<td>3.4</td>
<td>Representation of the MLE.</td>
</tr>
<tr>
<td>3.5</td>
<td>Recurrence plot of a time series: a) time series; b) recurrence plot.</td>
</tr>
<tr>
<td>3.6</td>
<td>Recurrence map from Fig. 3.5b in color.</td>
</tr>
<tr>
<td>3.7</td>
<td>The Swiss roll and the open box [101].</td>
</tr>
<tr>
<td>3.8</td>
<td>Two points on the Swiss roll. The Euclidean distance (dotted line) versus the geodesic distance (full line) [187].</td>
</tr>
<tr>
<td>3.9</td>
<td>Embedding the Swiss roll in 2 dimensions. The red line corresponds to the geodesic distance. It is shown in the reconstructed space (right) that the shortest distance between points is preserved (straight blue line) [187].</td>
</tr>
<tr>
<td>3.10</td>
<td>Illustration of the phase-space reconstruction.</td>
</tr>
<tr>
<td>3.11</td>
<td>Illustration of the phase shift (adapted from [180]).</td>
</tr>
<tr>
<td>3.12</td>
<td>a) The phase-space Duffing system in continuous form ($x_t$ versus $x_{t-1}$); b) the mutual information function with its minimum indicated by the dot.</td>
</tr>
<tr>
<td>3.13</td>
<td>Unfolding of the phase-space of the Duffing system ($x(t)$ versus $x(t-\tau)$).</td>
</tr>
<tr>
<td>3.14</td>
<td>Time series and local neighbors (adapted from [154]).</td>
</tr>
<tr>
<td>3.15</td>
<td>a) The Hénon map; b) results from the FNN test.</td>
</tr>
<tr>
<td>3.16</td>
<td>Delayed vector embedded in a) one dimension; b) two dimensions; c) three dimensions.</td>
</tr>
<tr>
<td>3.17</td>
<td>Recurrence plot of a section of the ElCentro 1940 NS component time series with an embedding dimension of: a) $d = 4$; b) $d = 6$; and c) $d = 8$.</td>
</tr>
<tr>
<td>3.18</td>
<td>Color map of Fig. 3.17b.</td>
</tr>
<tr>
<td>3.19</td>
<td>Schematic representation of the SOI algorithm.</td>
</tr>
<tr>
<td>3.20</td>
<td>Representation using local maps.</td>
</tr>
<tr>
<td>3.21</td>
<td>Time series responses.</td>
</tr>
<tr>
<td>3.22</td>
<td>Evolution of $\tau$ and $d$ for the dynamic inputs.</td>
</tr>
<tr>
<td>3.23</td>
<td>RMS error of the SOI algorithm for various sliding window sizes.</td>
</tr>
<tr>
<td>3.24</td>
<td>Stationarity index of local maps.</td>
</tr>
<tr>
<td>3.25</td>
<td>Identification of static $\tau$ and $d$ for a global representation.</td>
</tr>
</tbody>
</table>
3.26 3 DOF system controlled by an active system. a) Uncontrolled versus controlled case; b) Evolution of the embedding vector properties; c) Convergence of weights. Vertical lines indicate a node pruning; and d) Comparison with a pre-selected delay vector. ................................................... 137
3.27 3 DOF system controlled by an semi-active system. a) Uncontrolled versus controlled case; b) Evolution of the embedding vector properties; c) Convergence of weights. Vertical lines indicate a node pruning; and d) Comparison with a pre-selected delay vector. ................................................... 138
3.28 Performance of the SOI-WNN controller. a) Maximum inter-story displacements for various control strategies; and b) Comparison of network size for different delayed vectors. .................. 139
3.29 Evolution of the delayed vector: a) time delay; b) embedding dimension. ................................................................. 139
3.30 a) Time series of $\ddot{x}$; and b) the recurrence map for the pre-processed values of $\tau$ and $d$ ($\tau = 9$ and $d = 5$). .............. 140
3.31 Discretization of the time series. ........................................ 141
3.32 Local recurrence maps using the global values for $\tau$ and $d$. .. 141
3.33 Local recurrence maps using the average local values for $\tau$ and $d$ from the SOI algorithm: a) $\tau = 33$ and $d = 3$, b) $\tau = 28$ and $d = 4$; and c) $\tau = 18$ and $d = 5$. ................................. 141
3.34 Earthquake step-ahead predictions. a) San Fernando 1971; b) El Centro 1940; and c) Mexico City 1965. ............................ 143
4.1 a) Variable orifice damper [183]; and b) its simplified schematic [6]. ................................................................. 150
4.2 First large-scale application of a variable orifice damper in the US [177]. a) Installation; and b) variable orifice damper. ...... 150
4.3 Kajima Technical Research Institute AVS system. a) Structure with braces; b) close-up on the AVS system; c) illustration of the system in its locked position; and d) illustration of the system in its unlocked position (courtesy of Kajima Technical Research Institute). ................................................... 151
4.4 200 kN MR damper. ......................................................... 153
4.5 Bouc-Wen representation for the MR damper. .................... 154
4.6 SAIVS [135]. ................................................................. 155
4.7 VAD; $r$ is the gear radius [197]. ........................................ 155
LIST OF FIGURES

4.8 a) Electromagnetic friction damper [115]; b) SAEMFD [6]; and c) piezoelectric friction damper [142].

4.9 Large-scale application of an AMD to the Kyobashi Seiwa Building. a) Picture of the structure; b) schematic of the installation; and c) control diagram (courtesy of Kajima Technical Research Institute).

4.10 Structural equipped with the MR-TMD (MR damper not shown) [223].

4.11 Large-scale application of an MR-base isolation system. a) Picture of the structure; and b) 400 kN MR damper [177].

4.12 SCIS system [117].

4.13 CSD [157].

4.14 Configuration of MR, SMA, and FPB devices. [167].

4.15 Schematic representation of the dynamics of a) the MFD; and b) the MR damper.

4.16 Model fitting of a 55 kN friction-type device.

4.17 Dynamics of the MFD under a 7.62 mm amplitude sinusoidal excitation of 0.5 Hz: a) force-displacement; and b) force-velocity.

4.18 Schematic of the braking mechanism in the MFD.

4.19 Mark 50 draft gear [39].

4.20 Duo-servo drum brake: a) schematic; and b) force diagram.

4.21 Pressure distribution for duo-servo drum brake.

4.22 MFD behavior for a 100 kN required damping force under an harmonic excitation of 7.62 mm at 0.5 Hz: a) force-velocity; and b) voltage-velocity.

5.1 Elevation view of the simulated structure: a) X-direction; and b) Y-direction.

5.2 Toggle brace damper system [40].

5.3 Wind load used for the simulation. a) X-direction; and b) Y-direction.

5.4 Maximum acceleration profile, simulation 1: a) X-direction; and b) Y-direction.

5.5 Dynamics of the 10th MFD: a) linear actuation force-velocity; and b) voltage-velocity.

5.6 Maximum acceleration profile, simulation 2: a) X-direction; and b) Y-direction.

5.7 Maximum acceleration profile in X-direction, simulation 3.
<table>
<thead>
<tr>
<th>Figure</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>5.8</td>
<td>Comparison of hysteresis loops between the viscous damper and the MFD located between the 25th and the 26th floor: a) results from simulation 1; and b) results from simulation 3.</td>
</tr>
<tr>
<td>5.9</td>
<td>Network size and mitigation sensitivity in function of the linear constant for $\lambda$.</td>
</tr>
<tr>
<td>5.10</td>
<td>Network size and mitigation sensitivity in function of the minimum error $\eta$, with $\lambda = 100|P\mathbf{x}|_{\min}$.</td>
</tr>
<tr>
<td>5.11</td>
<td>Sensitivity of minimum error and distance parameters. a) Network size; and b) mitigation performance.</td>
</tr>
<tr>
<td>5.12</td>
<td>Sensitivity of pruning parameters. a) Network size; and b) mitigation performance.</td>
</tr>
<tr>
<td>5.13</td>
<td>Maximum 37th floor acceleration for various region bounds. a) Region $\mathcal{C}$, with region $\mathcal{C}_t = 1350$ kN; and b) region $\mathcal{C}_t$, with region $\mathcal{C} = 225$ kN.</td>
</tr>
<tr>
<td>5.14</td>
<td>Mitigation sensitivity in function of various region bounds.</td>
</tr>
<tr>
<td>5.15</td>
<td>Sensitivity of the sliding surface. a) Network size; and b) mitigation performance.</td>
</tr>
<tr>
<td>5.16</td>
<td>Evolution of the nodal weights for error weights on displacements and velocities being respectively: a) $10^2$ and $10^1$, MFD #1; b) $10^2$ and $10^1$, MFD #1; c) $10^1$ and $10^1$, MFD #1; and d) $10^1$ and $10^1$, MFD #10.</td>
</tr>
<tr>
<td>5.17</td>
<td>Sensitivity of the adaptation weights. a) Network size; and b) mitigation performance.</td>
</tr>
<tr>
<td>5.18</td>
<td>37th floor acceleration under various control strategies. a) At the beginning of the excitation; and b) after convergence.</td>
</tr>
<tr>
<td>5.19</td>
<td>Evolution of the input vector for the 10th controller.</td>
</tr>
<tr>
<td>5.20</td>
<td>Maximum 37th floor acceleration under time delay and random error. a) Random simulation 1; and b) random simulation 2.</td>
</tr>
<tr>
<td>5.21</td>
<td>Maximum acceleration profile, simulation 1: a) X-direction; and b) Y-direction.</td>
</tr>
<tr>
<td>5.22</td>
<td>Maximum acceleration profile, simulation 2: a) X-direction; and b) Y-direction.</td>
</tr>
<tr>
<td>5.23</td>
<td>Maximum acceleration profile in X-direction, simulation 3.</td>
</tr>
<tr>
<td>5.24</td>
<td>Maximum inter-story displacements of the top ten floors under various control strategies, Imperial Valley earthquake.</td>
</tr>
<tr>
<td>5.25</td>
<td>Evolution of the network sizes. Forgetting versus no forgetting feature.</td>
</tr>
</tbody>
</table>
LIST OF FIGURES

5.26 Plots of the relative performance indices $J/J_{viscous}$: a) near-field, $J_1$; b) near-field, $J_2$; c) mid-field, $J_1$; d) mid-field, $J_2$; e) far-field, $J_1$; and c) far-field, $J_2$. ............................................. 219

5.27 Mitigation performance and voltage: a) near-field, $J_1$; b) near-field, $J_2$; c) mid-field, $J_1$; d) mid-field, $J_2$; e) far-field, $J_1$; and f) far-field, $J_2$. ............................................. 221

5.28 Distributions of relative mitigation performances: a) $J_{1NF}/J_{1SOI}$; b) $J_{2NF}/J_{2SOI}$; c) $J_{1FI}/J_{1SOI}$; d) $J_{2FI}/J_{2SOI}$; e) $J_{1NSC}/J_{1SOI}$; and f) $J_{2NSC}/J_{2SOI}$. ............................................. 223

5.29 Average network size with and without the forgetting feature: a) near-field; b) mid-field; and c) far-field. ................................. 224

5.30 Performance of various controllers in function of estimation errors on the fundamental frequency, wind excitation. a) $J_3$; b) $J_4$; and c) $J_5$. ............................................. 225

5.31 Performance of various controllers in function of estimation errors on the fundamental frequency, wind excitation, $J_1$ and $J_2$. 227

5.32 Performance of various controllers in function of estimation errors on the fundamental frequency, earthquake excitation, $J_1$ and $J_2$. ............................................. 227

6.1 Mass ratio versus effective damping for two STMDs and a TMD [112]. ............................................. 239

A.1 Big Bear City earthquake: a) time series (unscaled); and b) maximum inter-story displacements of the top 10 floors under various control strategies. ............................................. 249

A.2 Chi-Chi earthquake: a) time series (unscaled); and b) maximum inter-story displacements of the top 10 floors under various control strategies. ............................................. 250

A.3 Coalinga earthquake: a) time series (unscaled); and b) maximum inter-story displacements of the top 10 floors under various control strategies. ............................................. 251

A.4 Coyote earthquake: a) time series (unscaled); and b) maximum inter-story displacements of the top 10 floors under various control strategies. ............................................. 252

A.5 Denali earthquake: a) time series (unscaled); and b) maximum inter-story displacements of the top 10 floors under various control strategies. ............................................. 253
A.6 Dinar earthquake: a) time series (unscaled); and b) maximum inter-story displacements of the top 10 floors under various control strategies. .................................................. 254

A.7 Duzce earthquake: a) time series (unscaled); and b) maximum inter-story displacements of the top 10 floors under various control strategies. .................................................. 255

A.8 Erzican earthquake: a) time series (unscaled); and b) maximum inter-story displacements of the top 10 floors under various control strategies. .................................................. 256

A.9 Friuli earthquake: a) time series (unscaled); and b) maximum inter-story displacements of the top 10 floors under various control strategies. .................................................. 257

A.10 Gilroy earthquake: a) time series (unscaled); and b) maximum inter-story displacements of the top 10 floors under various control strategies. .................................................. 258

A.11 Imperial Valley earthquake: a) time series (unscaled); and b) maximum inter-story displacements of the top 10 floors under various control strategies. .................................................. 259

A.12 Irpinia earthquake: a) time series (unscaled); and b) maximum inter-story displacements of the top 10 floors under various control strategies. .................................................. 260

A.13 Kern earthquake: a) time series (unscaled); and b) maximum inter-story displacements of the top 10 floors under various control strategies. .................................................. 261

A.14 Kobe earthquake: a) time series (unscaled); and b) maximum inter-story displacements of the top 10 floors under various control strategies. .................................................. 262

A.15 Kocaeli earthquake: a) time series (unscaled); and b) maximum inter-story displacements of the top 10 floors under various control strategies. .................................................. 263

A.16 Loma Prieta earthquake: a) time series (unscaled); and b) maximum inter-story displacements of the top 10 floors under various control strategies. .................................................. 264

A.17 Mammoth Lakes earthquake: a) time series (unscaled); and b) maximum inter-story displacements of the top 10 floors under various control strategies. .................................................. 265
LIST OF FIGURES

A.18 Manjil earthquake: a) time series (unscaled); and b) maximum inter-story displacements of the top 10 floors under various control strategies. 266

A.19 Michoacan earthquake: a) time series (unscaled); and b) maximum inter-story displacements of the top 10 floors under various control strategies. 267

A.20 Nahanni earthquake: a) time series (unscaled); and b) maximum inter-story displacements of the top 10 floors under various control strategies. 268

A.21 New Zealand earthquake: a) time series (unscaled); and b) maximum inter-story displacements of the top 10 floors under various control strategies. 269

A.22 Norcia earthquake: a) time series (unscaled); and b) maximum inter-story displacements of the top 10 floors under various control strategies. 270

A.23 Northridge earthquake: a) time series (unscaled); and b) maximum inter-story displacements of the top 10 floors under various control strategies. 271

A.24 Parkfield earthquake: a) time series (unscaled); and b) maximum inter-story displacements of the top 10 floors under various control strategies. 272

A.25 San Fernando earthquake: a) time series (unscaled); and b) maximum inter-story displacements of the top 10 floors under various control strategies. 273

A.26 San Francisco earthquake: a) time series (unscaled); and b) maximum inter-story displacements of the top 10 floors under various control strategies. 274

A.27 San Salvador earthquake: a) time series (unscaled); and b) maximum inter-story displacements of the top 10 floors under various control strategies. 275

A.28 Spitak earthquake: a) time series (unscaled); and b) maximum inter-story displacements of the top 10 floors under various control strategies. 276

A.29 Tabas earthquake: a) time series (unscaled); and b) maximum inter-story displacements of the top 10 floors under various control strategies. 277
A.30 Victoria earthquake: a) time series (unscaled); and b) maximum inter-story displacements of the top 10 floors under various control strategies.
List of Tables

1.1 Classification of contributions in the closed-loop control system. 43

3.1 RMS error of the controller over various input strategies \((\times 10^{-5})\) 131
3.2 Average delay vector parameters. 143

4.1 Passive energy dissipation systems \([182]\). 148
4.2 Technical characteristics of a 200 kN MR damper \([212]\). 152
4.3 MFD 200 kN parameter values. 166

5.2 Fundamental periods and comparison with values reported in \([126]\) from a wind tunnel testing. 183
5.1 Dynamic properties. \(K\) is the stiffness, \(C\) is the damping, \(M\) is the mass, subscripts \(X\) and \(Y\) represent the \(X\) and \(Y\) directions, and subscript \(\theta\) represents rotational. 184
5.3 Configuration of viscous dampers 185
5.4 List of simulated earthquakes. 187
5.5 Summary of the performance indices. 188
5.6 Configuration of MFDs for each simulations. 189
5.7 Maximum acceleration at the 37th floor. 192
5.8 Maximum increase in temperature \((^\circ C/50\ \text{sec})\). 193
5.9 Maximum inter-story displacement. 194
5.10 Maximum absolute acceleration. 195
5.11 List of non-adaptive parameters for 1350 kN MFDs. 196
5.12 Control strategies used for performance comparison. 206
5.13 Performance indices for wind mitigation, simulation 1, \(X\)-direction. 207
5.14 Performance indices for wind mitigation, simulation 1, \(Y\)-direction. 209
5.15 Performance indices for wind mitigation, simulation 2, \(X\)-direction. 210
5.16 Performance indices for wind mitigation, simulation 2, \(Y\)-direction. 210
5.17 Performance indices for wind mitigation, simulation 3. 211
5.18 Maximum acceleration at the 37th floor. 211
5.19 Performance indices for earthquake mitigation (Imperial Valley), simulation 4. 214
5.20 Relative mitigation performance over viscous strategy for all earthquakes, J1. .............................................. 217
5.21 Relative mitigation performance over viscous strategy for all earthquakes, J2. .............................................. 218
5.22 Relative mitigation performance over viscous strategy for all earthquakes, J2. .............................................. 222

6.1 Comparison of large-scale variable friction devices. .............. 231
6.2 Comparison of online sequential intelligent controllers. ........... 232
6.3 Neurocontroller parameters for a feedforward single-layer wavelet neural network. ........................................... 234
6.4 Cost analysis of passive viscous versus MFD control strategies 240

A.1 List of simulated earthquakes. ........................................ 248
A.2 Performance indices, Big Bear City Earthquake, simulation 4. 249
A.3 Performance indices, Chi-Chi Earthquake, simulation 4. ......... 250
A.4 Performance indices, Coalinga Earthquake, simulation 4. ..... 251
A.5 Performance indices, Coyote Earthquake, simulation 4. ..... 252
A.6 Performance indices, Denali Earthquake, simulation 4. ....... 253
A.7 Performance indices, Dinar Earthquake, simulation 4. ......... 254
A.8 Performance indices, Duzce Earthquake, simulation 4. ......... 255
A.9 Performance indices, Erzican Earthquake, simulation 4. ....... 256
A.10 Performance indices, Friuli Earthquake, simulation 4. ....... 257
A.11 Performance indices, Gilroy Earthquake, simulation 4. ....... 258
A.12 Performance indices, Imperial Valley Earthquake, simulation 4. 259
A.13 Performance indices, Irpinia Earthquake, simulation 4. ....... 260
A.14 Performance indices, Kern Earthquake, simulation 4. ......... 261
A.15 Performance indices, Kobe Earthquake, simulation 4. ....... 262
A.16 Performance indices, Kocaeli Earthquake, simulation 4. ...... 263
A.17 Performance indices, Loma Prieta Earthquake, simulation 4. . 264
A.18 Performance indices, Mammoth Lakes Earthquake, simulation 4. 265
A.19 Performance indices, Manjil Earthquake, simulation 4. ...... 266
A.20 Performance indices, Michoacan Earthquake, simulation 4. . 267
A.21 Performance indices, Nahanni Earthquake, simulation 4. ... 268
A.22 Performance indices, New Zealand Earthquake, simulation 4. . 269
A.23 Performance indices, Norcia Earthquake, simulation 4. ....... 270
A.24 Performance indices, Northridge Earthquake, simulation 4. ... 271
A.25 Performance indices, Parkfield Earthquake, simulation 4. ... 272
<table>
<thead>
<tr>
<th>Table</th>
<th>Description</th>
<th>Page</th>
</tr>
</thead>
<tbody>
<tr>
<td>A.26</td>
<td>Performance indices, San Fernando Earthquake, simulation 4.</td>
<td>273</td>
</tr>
<tr>
<td>A.27</td>
<td>Performance indices, San Francisco Earthquake, simulation 4.</td>
<td>274</td>
</tr>
<tr>
<td>A.28</td>
<td>Performance indices, San Salvador Earthquake, simulation 4.</td>
<td>275</td>
</tr>
<tr>
<td>A.29</td>
<td>Performance indices, Spitak Earthquake, simulation 4.</td>
<td>276</td>
</tr>
<tr>
<td>A.30</td>
<td>Performance indices, Tabas Earthquake, simulation 4.</td>
<td>277</td>
</tr>
<tr>
<td>A.31</td>
<td>Performance indices, Victoria Earthquake, simulation 4.</td>
<td>278</td>
</tr>
</tbody>
</table>
1 Introduction
CHAPTER 1. INTRODUCTION

Chapter Notation

\(\sigma\) displacement 
\(\Delta_a\) actuator dynamic uncertainty 
\(\Delta_p\) parametric uncertainty 
\(f\) state function 
\(t\) time 
\(u\) input or forcing 
\(w\) disturbance 
\(x\) state 
\(x_d\) distance 
\(C\) damping matrix 
\(D\) disturbance 
\(F\) force application matrix 
\(F_D\) disturbance application matrix 
\(K\) stiffness matrix 
\(M\) mass matrix 
\(\mathbb{R}\) set of real numbers

1.1 Why Feedback Control for Civil Structures?

Traditional structural design methods are based on a strength-based approach, where members are sized in order to be capable of resisting the energy from internal and external loads. Recently, an alternative has been proposed: the performance-based design [41]. Performance-based design is a design approach that satisfies motion constraints as its primary goal, and then verifies for strength [40]. The approach is traditionally executed by appropriately sizing stiffnesses, but recently, passive energy dissipation systems such as hysteretic and viscous dampers, tuned-mass dampers, and base-isolation systems have gained popularity and are used in many buildings [68, 177, 143]. Passive energy dissipation strategies have the important benefit of energy extraction, thus improving the efficiency of structural systems against natural hazards. More effective structural systems generally allow structures to be conceived with less material, which results in more effective and sustainable systems.

Semi-active and active energy dissipation systems, or feedback control systems, have been shown to outperform purely passive systems. A good
1.1. WHY FEEDBACK CONTROL FOR CIVIL STRUCTURES?

Figure 1.1: Cable displacement in function of devices location [80].

example is found in Johnson et al. [80]. The authors have studied the performance of passive, semi-active, and active control systems for damping of stay cables vibrations as a function of the device location along the length of the cable $x_d$. Their study was centered on the infamous Dongting Lake Bridge in China, a cable stayed bridge featured the very first application of magnetorheological (MR) damping systems to civil structures [35]. Fig. 1.1 illustrates the performance of various damping strategy for mitigation of the cable displacement (RMS cable displacement $\sigma_{\text{displacement}}$). The performance of the semi-active control strategy is significantly better than a passive strategy (87% reduction for the semi-active case versus 58% reduction for the passive case at $x_d = 0.02$), and the semi-active strategy only requires a fraction of the power required from the active strategy as it can be operated on batteries.

The general performance of active and semi-active systems is similar to the one from the previous example: active control systems are capable of sufficient mitigation performance, and semi-active systems provide a performance closer to an active system, but by requiring less energy input.

While it seems that feedback control systems represent the next logical step in improving structural system efficiencies, these control systems are not yet widely accepted by the construction and civil engineering fields. In Section 1.2, we will discuss what impedes their acceptability. The problem
statement, or what we are trying to achieve here, will follow in Section 1.4, where we will spoil any suspense by describing our proposed solutions and contributions. Section 1.5 discusses our choice for the main simulations, or why we have decided not to use one of the field’s benchmark problems. Section 1.6 presents some notes on the terminology employed throughout the text. Section 1.7 concludes the introduction chapter by explaining the organization of the dissertation.

1.2 Control of Uncertain Systems: The Civil Engineering Challenge

The field of control has thoroughly been developed since Norbert Wiener proposed to unify the field of feedback control under cybernetics [202], and has been widely extended to most engineering field. Its application to civil engineering can be traced up to Nordell in 1969 [144] with the use of active tendons to protect structures from blast. Yao formally introduced the concept of structural control in 1972 [217]. Since, several control strategies using active and semi-active control have been researched, but the physical implementation of those control strategies to large-scale civil structures has been limited. The very first application was achieved in 1989 in Tokyo by the Kajima Corporation, and consisted of an active mass driver installed at the top of the ten-story Kyobashi building [89]. In an extensive review of the structural control field in 2003, Spencer & Nagarajaiah [177] reported that there were over 50 large-scale applications of feedback control systems in civil structures. In their paper, the authors noted that none of the application was in the United States, and alleged that possible reasons include conservatism of the construction industry with respect to technologies, as well as lack of research and development expenditures. Nevertheless, the field of structural control has attracted a lot of attention over the last decades in search of robust and performing strategies for vibration mitigation.

The field of control engineering counts numerous control algorithms developed for diverse applications, but significant work remains to be done for strategies applicable to civil structures. In effect, the field of structural control has specific challenges in every step of the feedback control loop. For instance, take a typical closed-loop control system as represented in Fig. 1.2. Excitations are often unmeasurable, especially in the case of wind excitations.
CONTROL OF UNCERTAIN SYSTEMS: THE CIVIL ENGINEERING CHALLENGE

Controlled systems, also termed plants, are very large, and often unknown. Sensors are limited due to the numerous degree-of-freedoms. Control devices have large power requirements. Controllers, to be efficient, must integrate all those challenges in their design. Furthermore, there are practical obstacles or difficulties in implementing control systems in civil structures. Those include software-hardware integration, limited number of sensors and actuators, complex actuator dynamics, large actuation force required, and need of a fail-safe control system [38, 175]. Thus, we can easily argue that the control challenges in civil engineering are different from other fields, which impede the acceptability of control strategies for civil structures. This applicability concern is rarely discussed in research papers proposing control algorithms for semi-active and active control of civil structures [209, 175]. In what follows, we review in detail the primary challenges that are field-specific to structural control.

1.2.1 Model Uncertainties

The problem of model uncertainties for large-scale systems is a non-trivial challenge and is the primary feature that gave rise to our interest in studying control systems for civil structures. Several papers propose control algorithms where they assume knowledge of structural dynamic properties: stiffnesses,
damping, and masses. However, such parametric properties are difficult to estimate, and the uncertainties can be quite large [181, 78]. In essence, we deal with systems that have large parametric uncertainties. In addition, there exists sources of nonlinearity and measurement noises that are not necessarily taken into account, such as actuator dynamics, sensor inaccuracies, and time delay induced in the control loop [54]. Optimal control algorithms are designed based on the model estimations, and their efficiency is dependent on the accuracy of the estimations.

1.2.2 Sensors and Observers

State measurements and observations are essential features to feedback control systems. Several control algorithms proposed in the literature assume full state feedback, but this assumption rarely holds in the case of large-scale systems. States are measured using sensors or observers. If we consider available sensor hardware, most measurement methods for displacements and velocities give only relative measures, and therefore require placement of sensors on every degree-of-freedom from the bottom up to the last state being fed back [127]. In practice, such a strategy is not easy and can be quite expensive [155]. Accelerometers, on the other hand, are cheap, small, and widely employed [36, 163], but their application results in a complex wiring network or technological challenge for wireless transmission of packets. Feedback systems for civil structures relying on pure acceleration feedback are more robust [129], but controlling for acceleration is equivalent to controlling for mass, which can be significantly inefficient.

Another strategy is to derive displacement and velocity states from acceleration data, which can be challenging. Integration of acceleration is not practical and leads to numerical integration errors [79]. Observers can be designed, but they could possibly required large computation time [43]. We also note that conventional observers need knowledge of the system dynamics. Alternatively, adaptive observer can be designed for tuning to an unknown system [138].

1.2.3 Actuators

Provided that we were convincing with the arguments in favor of semi-active and active structural control, the choice of the type of actuator is not trivial. Here, the term actuator is used loosely, and refers to a control device that can
be activated electrically. Several research papers introduce control strategies with different types of actuators, but many of those strategies fail to meet practical requirements of large force capability, mechanical reliability and robustness of actuators [189].

Power requirement is a specific issue arising from the large size of plants being controlled [226]. During extraordinary events such as earthquake, there is a high occurrence probably of a general power failure. It is therefore essential that actuators be capable of running on a secondary power system, which may result in a lower actuation capacity.

Mechanical reliability and robustness of actuators is a primary concern for control of large-scale structures. For instance, failure of an engine on an aircraft can be catastrophic. The same idea extends to civil structures, whereas actuators must be physically capable of exerting a force in the occurrence of a moderate-to-extraordinary load to ensure serviceability and safety. The use of an active control scheme may lead to instabilities if the controller is not robust enough with respect to system uncertainties. This brings a substantial advantage of semi-active control schemes: the dynamics of civil structures is inherently stable. In other words, the use of semi-active devices cannot destabilize a controlled system, and the worst-case scenario is an uncontrolled structure.

1.2.4 Controllers

The controller is somewhat the brain of the feedback control mechanism. It has to request actions to the control device based on the system states, and thus integrates all of the closed-loop components in its control rule. Considering the obstacles we have discussed so far, we are interested in systems with large-parametric uncertainties, with limited state measurements, and that are equipped with semi-active damping devices. Thus, we need controllers capable of efficiently mitigating vibrations for unknown systems, equipped with semi-active devices, and with limited measurements.

Controllers can be divided into two mutually exclusive classes: fixed parameters controllers and adaptive controllers. Fixed parameters controllers include modern deterministic control methods such as $H_2, H_\infty$, Lyapunov-based (including sliding mode control), and stochastic methods. Adaptive controllers include some specialized variants of the previously enumerated controllers, model reaching adaptive controllers (MRAC), self-tuning controllers, and intelligent controllers. Intelligent controllers are a special form of adaptive
controllers that typically aim at constructing their own representation of the control rule.

The topic of control is central in this thesis. Here, we introduce broad concepts of different general types of controller in order to discuss their applicability to control of large-scale uncertain systems. That discussion will be useful for understanding the directions of this thesis. Chapter 2 provides a more intensive discussion on their possible applications to uncertain systems.

**Fixed Parameters Controllers**

The first type of fixed parameters controllers are optimal controllers. Optimal controllers, among which $H_2$ and $H_\infty$, are designed by minimizing cost functions. Typically, full parametric knowledge is necessary for constructing the cost function. They are certainly not suited for control of uncertain civil structures. A next class of controller introduces some level of uncertainty: robust controllers. They also include the infamous $H_2$ and $H_\infty$ controllers, which are designed using techniques such as loop recovery, residual feedback, or frequency shaping [10]. In this thesis, to avoid confusion, we will always refer to $H_2$ and $H_\infty$ as robust controllers, and let optimal controllers be their own set, used with full parametric knowledge. Robust control has been widely researched, and several papers have shown their capabilities for large-scale systems with parametric uncertainties [198, 199].

Next, we have Lyapunov-based methods, such as linearized feedback and sliding mode control [171, 37]. Sliding mode controllers have been widely used in civil structures for their great capabilities to handle system nonlinearities, their intuitive concept of energy extraction, and their enhanced stability with respect to large uncertainties. Stochastic control techniques are also popular methods for controlling systems with probabilistic uncertainties. However, they require prior knowledge on the statistical distribution of parameters [13].

In the context of large-scale systems with large uncertainties, we are required to use controllers with large robustness. Unfortunately, the performance of a controller may decrease with the increased level of uncertainty. If we consider very large uncertainties, on the level of 20% to 40%, or even unknown systems, adaptive controllers could be more appropriate.
Adaptive Controllers

Adaptive control methods can be divided in two distinct families: indirect and direct control. Indirect control consists of controlling plants by identifying unknown parameters. This identification is typically achieved by synchronizing to a model with a similar dynamics, with its associated popular technique: model reaching adaptive controllers (MRAC). Conversely, direct control directly adapts or tunes control parameters, and uses techniques such as self-tuning controllers (STC).

As we will see in Chapter 2, MRAC is quite appealing in control of unknown systems, because it allows the evaluation of the parametric properties of the system provided that the excitation is rich enough. Thus, it may also, ideally, be used for structural health monitoring. The main issue with the technique is that any force input needs to be known. Song et al. [173] clearly identified the same issue for control of car suspension systems, as it is merely impossible to measure the excitation arising from the road geometry. In civil structures, only earthquake excitations could be appropriately measured, during which parameter estimations is not of primary concern in a control point of view. Moreover, identifying or testing the structure using known external excitations such as a shaker is not technically and economically appealing.

Thus, we might be more interested by direct control methods. The adaptation of STC can be done using batch processing or sequential adaptation. Batch processing assumes sets of inputs-outputs (forces-states) that are already available and the controller is directly adapted by pre- or post-processing. Such scheme necessitates prior set of data, which again is practically unrealistic for large-scale systems due to the economically and technically difficult task of gathering those sets. Sequential adaptation takes input-output sets as they come, and adapts the controllers as the excitation goes. However, sequential adaptation is constrained by a need for control performance during the excitation.

Direct parameter estimation for STC can be realized using mathematical or non-mathematical models. Mathematical representation of controlled plants can, for instance, be achieved by recursive least-square, recursive extended least square, recursive instrumental variables, recursive maximum likelihood, and stochastic approximation [172]. However, sequential estimation would require significant computation time due to the size of civil structures, which could induce time delay in the system and can lead to instabilities [40]. On the other hand, non-mathematical models, including genetic algorithms,
fuzzy logic and neural networks, can be used to build representations. They are often refer as intelligent controllers because of their ability to optimize controllers based on machine learning techniques. Advantages of intelligent controllers include [77]:

1. tolerance to model uncertainties
2. less prior knowledge required
3. capacity to handle nonlinearity
4. possibility of quick convergence

Genetic algorithms (GA) have shown good performance at system identification and control, but they generally require a very long computation time and have a high possibility to end up in a local minima [16]. Adaptive fuzzy logic is a set of control rules based on the system states where these rules are adaptable. Classical fuzzy controllers are criticized for their lack of systematic design and stability proof [72]. An adaptive neural network is a mathematical representation of the system evolving with time. The outputs of the neural nets are a linear combination of linear or nonlinear functions. Analogous to GA, they may also converge to local minima.

1.3 Problem Statement

The problem statement can be written as follows. We need to design a feasible feedback control strategy for a system with:

1. very-large geometric properties (large-scale)
2. large parametric uncertainties
3. limited state measurements
4. unique mechanical requirements for the actuators

By feasible, we mean a strategy that thoroughly integrates economical and technical constraints (such as power requirement, sensor hardware, mechanical and electrical reliability, etc.). Our objective is to enhance the applicability and acceptability of feedback control systems to civil structures by proposing
1.3. PROBLEM STATEMENT

an integrated closed-loop control system for large-scale structures with large parametric uncertainties.

Mathematically: for a given actuator dynamics that has uncertainties on its dynamics $\Delta_p$ and force reachability $\Delta_a$, we need to design a controller that stabilizes:

$$(M + \Delta_p M)\ddot{x} + (C + \Delta_p C)\dot{x} + (K + \Delta_p K)x = F(u + \Delta_a u) + F_D D \tag{1.1}$$

where $M, C, K$ are the mass, damping, and stiffness matrices respectively, $x$ is the displacement vector, $\Delta_p$ is the parametric uncertainty matrix, $F$ is the force application matrix, $F_D$ is the disturbance application matrix, $u$ is the force input vector, and $D$ is the disturbance matrix. The control force is given by:

$$u = f(x, t) \tag{1.2}$$

where $f$ is a nonlinear function, and $t$ represents time.

Assuming that $\Delta_a$ is known and bounded, three different classes of control problems are associated with (1.1):

1. $\Delta_p$ is known
2. $\Delta_p \in [\Delta_p^-, \Delta_p^+]$
3. $\Delta_p \in \mathbb{R}$ and bounded

Classes 1 and 2 imply that an estimation of the dynamic properties is available, while class 3 is a more general control problem where the bound on uncertainty is unknown. In that last class, we generalize that no prior information on the plant dynamics is available.

It results that the choice of controller depends on the level of system uncertainty and desired robustness. Fig. 1.3 classifies types of controllers in function of parametric uncertainties and desired robustness for each control class. In the case of civil structures, it has been previously argued that parametric uncertainties exist and are large. Thus, civil structures find themselves in classes 2 and 3, where most of the fixed parameters controllers can be inefficient. For class 3 problems, the level of desired robustness is invariably high, as one needs stability with respect to natural hazards and parameters estimation error.
Before defining our proposed control system and contributions, we shall clarify our classification of controllers with a short numerical example.

### 1.3.1 Numerical Example

We here use a simple numerical example to illustrate the concept of controller robustness versus parametric uncertainties. Three different algorithms have been investigated on a three degree-of-freedom system. The system is a scaled model of a structure used in Laflamme et al. [97] and is subjected to the El Centro 1940 North-South component earthquake. The plant parameters are taken as:
1.3. PROBLEM STATEMENT

\[
M = \begin{bmatrix}
98.3 & 0 & 0 \\
0 & 98.3 & 0 \\
0 & 0 & 98.3 \\
\end{bmatrix} \text{ kg}
\]

\[
C = \begin{bmatrix}
175 & -50 & 0 \\
-50 & 100 & -50 \\
0 & -50 & 50 \\
\end{bmatrix} \text{ N} \cdot \text{s/m}
\]

\[
K = \begin{bmatrix}
12.0 & -6.84 & 0 \\
-6.84 & 13.7 & -6.84 \\
0 & -6.84 & 6.84 \\
\end{bmatrix} \times 10^5 \text{ N/m}
\]

A 1000 N magnetorheological (MR) damper is installed between the basement (ground) and the first story. For the investigation, the required forces from the controller are sent to the MR damper. The input amperage is selected following a saturation rule, where it is set as maximum if the the required force is of the same sign and greater in absolute value than the current force, and is taken as zero otherwise.

A classical optimal controller, the LQR controller, is designed based on parameter estimations ranging from 0% to 100% of the true natural frequency. A first simulation is conducted using the LQR controller by itself. A second simulation uses the same LQR controller, but augmented by an SMC, which is hypothesized to be more robust. The third simulation uses the LQR controller augmented by an intelligent controller, the wavelet neural network (WNN) as introduced in [97] and presented in Chapter 2. The neurocontroller is a single hidden layer feedforward network whose nodes are constructed with wavelet functions and have the capacity to adapt the center, bandwidth, and weights. Displacement and acceleration mitigation results for the three cases are shown in Fig. 1.4a and Fig. 1.3b respectively.

The robustness of a controller is here define as a low variation of the mitigation performance with respect to estimation errors. Results from displacement mitigation in Fig. 1.4a show that the pure LQR is robust up to a 12% variation in the natural frequencies, representing a 11% over estimation of masses and underestimation of stiffnesses. The LQR-SMC is robust up to 41%, representing a 33% overestimation of masses and underestimation of stiffnesses. The LQR-WNN is robust up to 83%, representing a 53% overestimation of masses and underestimation of stiffnesses. A similar trend is observed for acceleration mitigation in Fig. 1.3b.
CHAPTER 1. INTRODUCTION
1.3. PROBLEM STATEMENT

Figure 1.3: Mitigation results: a) Maximum displacement (cm); and b) maximum acceleration (cm/s²).
1.4 Proposed Control System & Contributions

The application of semi-active and active control systems in civil engineering is in its infancy. There is a strong argument that control of civil structures could, in addition to enhanced efficiency of structural systems for serviceability and strength, lead to material savings. This is the promise of a performance-based design approach, which allows the engineers to first design a structure according to performance criteria, such as maximum acceleration and/or maximum inter-story displacements, and verify strength criteria as a second step [195]. For several examples of successful performance-based approaches, the reader is referred to [40].

The main objective of this thesis is to enhance the applicability of control systems for civil engineering applications, and thus propose a general approach for large-scale controlled systems. Following the discussion on the control problem for large-scale structures, we feel that there is a need to look at the entire closed-loop control system of a large-scale structure in order to propose a feasible control solution. It results that the issue of applicability is made central throughout the thesis.

The proposed integrated control system consists of an adaptive controller designed for semi-actively controlled unknown systems using limited measurements. Despite that the level of uncertainty of the controlled systems could be relaxed from class 3 to class 2, even in the case of large uncertainties (of the level 50%, for instance), this thesis does not so. The intellectual merit does not target to tune a control system for an optimal performance, but to propose a new type of controller that is tailored to the control challenges in large-scale systems. It is up to the reader to decide whether or not the controller could augment a primary controller to account for large uncertainties. In addition to a new controller, a novel semi-active control device is proposed, as a feasible controller would be useless without a mechanically reliable technology. Here again, the damping device is used without any other damping systems. Nevertheless, hybrid applications of with the proposed device would be intellectually thrilling.

To be more specific, the main contributions of the thesis are as follows. We propose both a new type of adaptive controller and a new semi-active mechanical device. The controller consists of an adaptive wavelet neural network. It is novel by its capability to self-organize the input space, using the Self-Organizing Inputs (SOI) algorithm. The SOI has been developed by the
Table 1.1: Classification of contributions in the closed-loop control system.

<table>
<thead>
<tr>
<th>object &amp; sensors</th>
<th>novelty</th>
<th>problem addressed</th>
<th>contribution field</th>
</tr>
</thead>
<tbody>
<tr>
<td>controller</td>
<td>SOI</td>
<td>limited measurements</td>
<td>intelligent control &amp; structural control</td>
</tr>
<tr>
<td>&amp; sensors</td>
<td></td>
<td></td>
<td>structural control</td>
</tr>
<tr>
<td>controller</td>
<td>WNN + SC</td>
<td>unknown dynamic response &amp; semi-active adaptation</td>
<td>structural control</td>
</tr>
<tr>
<td>control device</td>
<td>MFD</td>
<td>semi-active devices</td>
<td>mechanical damping devices</td>
</tr>
<tr>
<td>entire loop</td>
<td>enhanced applicability</td>
<td>implementation</td>
<td>structural system efficiency</td>
</tr>
</tbody>
</table>

author as a tool to optimize general black-box representations with unknown input-output data sets, and is here applied to the case of an adaptive neural net. It allows the controller to use limited measurements. It is also novel by its application to semi-active control systems, which is achieved by augmenting the controller by a sliding controller (SC), which allows the adaptive scheme to adapt even if a control device has a limited force reachability (semi-active dampers cannot add energy to a system). The proposed semi-active device is a variable friction damper, termed the Modified Friction Device (MFD). It is novel by its capability to realistically output large resisting loads (in the order of $10^5$ N) using only reliable and robust mechanical technologies. Finally, it is argued that the entire control system is a promising strategy for creating more effective structural systems. The contributions of this thesis are summarized in Table 1.1.

### 1.5 Benchmark Problems and Simulations

The large-scale nature of civil structures makes testing an economically and technically challenging task. Testing of control systems on full-scale structures might result in more accurate results and enhance the acceptability of a control scheme, but the cost associated with construction and operation of testing facilities is discouraging, and might not make engineering sense. Computer simulations have been developed, and their level of accuracy is beyond acceptability, provided that the models are right.

Given that computer simulations are accurate, one needs to create models for conducting simulations. Several benchmark problems have been proposed in the literature to allow comparison of control systems within the structural control community. They represent a serious effort to unify the field and enhance the acceptability of control schemes for civil structures. For instance, Ohtori et al. [147] proposed a benchmark for seismically excited nonlinear

The problems with these benchmark models are in their specificities. Comparing control systems for specific problems often boils down to a problem of parametric adjustments of a proposed control algorithm. For instance, once could propose an LQR control algorithm, and tune the control weight matrices until the control objectives are attained, or better than other proposed algorithms. Moreover, we argue in this thesis that civil structures have dynamics that are difficult to estimate. Despite that some of the benchmark problems do allow for some level of uncertainties, control schemes use data that can be inaccurately far from possible estimations in real-life situations. For those reasons, a new generation of benchmark models might be necessary to enhance the acceptability of semi-active, hybrid, and active control systems in the community. For instance, a benchmark model could include high uncertainty and a certain level of randomness in the parameters or the excitations themselves, which would help comparing robustness of the proposed control strategies. Nevertheless, constructing such benchmark is out-of-the-scope of our work.

This thesis proposes a control scheme for unknown systems. For applicability concerns, there is a considerable effort to maintain all the non-adaptive controller parameters constant or rule-specific for all types of simulations. It is therefore impossible (or unfair) to compare with other control systems found in the benchmark problems. We have preferred to use our own numerical model. The main simulations for our proposed control system will be conducted on an existing structure located in Boston, MA. The choice of the model is motivated by the availability of the engineering data, and the passive viscous damping system currently installed in the structure. That provides an excellent opportunity to assess the performance of a semi-active control system by comparing with the passive system. A more extensive description of the structure will be provided in Chapter 5.
1.6 Notes on Terminology

We judge important to clarify some general terminology used throughout this thesis. First, the term *Intelligent Systems* is utilized in many fields for various topics. Here, we use it in the context of control systems. Despite that its applications are numerous, the techniques, methods, and algorithms used within the general concept of intelligent systems are similar across fields. For instance, in machine learning, we could talk about an agent that learns planning actions based on goals. In control, we would say that a plant adapts its control rules based on performance. Several research papers are actually written cross-fields and most of those terms are used interchangeably, just like we will do in this thesis. Popular ones are: learning and adaptation, actions and inputs, goals and performances.

In addition, the term *intelligent* is itself confusing and may lead to several misconception. In structural control, *intelligent* is not typically used in opposition to *stupid*, or in the sense of *smart*. *Intelligent systems* refer to adaptable systems, or systems built with an underlying algorithm that has the capacity to adapt to its environment. As far as we are concerned, intelligent systems can be used as a synonym of adaptive systems. The term *smart* refers to the utilization of smart materials, such as shape memory alloys and piezoelectric materials. Those materials are actually inert (there is nothing smart about them!), but their properties can be changed using electrical inputs (heat, currant, or magnetism). For instance, the paper title [99] *Intelligent Controller for Smart Base Isolation of Masonry Structures* makes that interpretation clear: intelligence refers to the adaptive capability of the controller, and smart refers to the utilization of a magnetorheological damper in the base-isolation system.

The reader will also notice that the field of control contains several terms that are inspired by biology: genetic algorithms inspired by genetic evolution, neural networks inspired by neurons, fuzzy logic inspired by human decision processes, among others. In this thesis, we are presenting a type of neural network for control of unknown system. Neural networks, as we will see, are nothing more than a linear combination of linear or nonlinear equations. They are a useful way to graphically represent such combination, which graphical representation is based on human neurons. The reader must keep that concept in mind: a neural net that converges is a representation of a system in form of an equation. We will use those two concepts interchangeably, where neural
CHAPTER 1. INTRODUCTION

nodes will be equivalent to mathematical terms.

1.7 Organization of the Dissertation

The thesis is organized as follows.

Chapter 2 reviews some basic control theory concepts and algorithms, and discusses their applicabilities to control of uncertain systems. The main contribution of the chapter is a modified wavelet neurocontroller (WNN) tailored to semi-active control systems.

Chapter 3 discusses the problem of input selection for black-box representation, develops the novel self-organizing input (SOI) algorithm, and demonstrates some basic performance when used along with the WNN from Chapter 2. The controller will be abbreviated SOI-WNN.

Chapter 4 brings the reader away from control theory into the kingdom of control devices and strategies for large-scale civil structures. The chapter proposes the new mechanical damping device termed the modified friction device (MFD).

Chapter 5 takes the SOI-WNN and simulates its performance using the MFD as an integrate semi-active control system with limited state measurements. The simulation is conducted on an existing 39-story building located in Boston, MA.

Chapter 6 discusses the findings from the simulations, and potential impacts.

Chapter 7 concludes the thesis. Fig. 1.4 schematises the organization of the thesis for clarity.
1.7. ORGANIZATION OF THE DISSERTATION

Figure 1.4: Organization of the theoretical chapters.
Control Algorithms for Large Parametric Uncertainties
### Chapter Notation

<table>
<thead>
<tr>
<th>Symbol</th>
<th>Description</th>
<th>Symbol</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\alpha_0$</td>
<td>scale parameter</td>
<td>$r$</td>
<td>reference signal</td>
</tr>
<tr>
<td>$\eta$</td>
<td>positive constant</td>
<td>$s$</td>
<td>sliding surface</td>
</tr>
<tr>
<td>$\gamma$</td>
<td>weights</td>
<td>$t$</td>
<td>time</td>
</tr>
<tr>
<td>$\lambda$</td>
<td>threshold or</td>
<td>$u$</td>
<td>force input</td>
</tr>
<tr>
<td></td>
<td>sliding surface weights</td>
<td>$\tilde{u}$</td>
<td>force error</td>
</tr>
<tr>
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<td>Euclidean location</td>
<td>$u_b$</td>
<td>force bound</td>
</tr>
<tr>
<td>$\nu$</td>
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<td>actual force</td>
</tr>
<tr>
<td>$\phi$</td>
<td>wavelet function</td>
<td>$u_{\text{req}}$</td>
<td>required force</td>
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<td>$u_{\text{SL}}$</td>
<td>sliding surface force</td>
</tr>
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<td>$\sigma$</td>
<td>bandwidth</td>
<td>$u_{\text{NN}}$</td>
<td>neural network force</td>
</tr>
<tr>
<td>$\omega$</td>
<td>frequency</td>
<td>$x$</td>
<td>state</td>
</tr>
<tr>
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<td>positive constant or</td>
<td>$x_d$</td>
<td>desired state</td>
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<td>aggregation of $\gamma$ and $\phi$</td>
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<td>wind</td>
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</tr>
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</tr>
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<td>$\Phi$</td>
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<td>dictionary of wavelets</td>
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</tr>
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<td></td>
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</tr>
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<td>number of nodes</td>
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</tr>
<tr>
<td>$j$</td>
<td>imaginary number</td>
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</tr>
<tr>
<td>$k$</td>
<td>stiffness or constant</td>
<td></td>
<td></td>
</tr>
<tr>
<td>$m$</td>
<td>mass or transition function</td>
<td></td>
<td></td>
</tr>
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<td>$n$</td>
<td>number</td>
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</tr>
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<td>state-space matrix</td>
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<td>$B$</td>
<td>general force input matrix</td>
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<td>$B_f$</td>
<td>actuation force input matrix</td>
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<td>$B_g$</td>
<td>ground force input matrix</td>
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</tr>
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<td>$B_w$</td>
<td>wind force input matrix</td>
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</tr>
<tr>
<td>$C$</td>
<td>stiffness matrix</td>
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<td></td>
</tr>
<tr>
<td>$E$</td>
<td>vector of ones</td>
<td></td>
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</tr>
<tr>
<td>$F$</td>
<td>force application matrix</td>
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</tr>
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<td>gain matrix</td>
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<td>transfer function</td>
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<td>identity matrix</td>
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<td>Jacobian</td>
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<td>$K$</td>
<td>stiffness matrix</td>
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</tr>
<tr>
<td>$L$</td>
<td>perturbed gain</td>
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<tr>
<td>$L_0$</td>
<td>unperturbed gain</td>
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<td></td>
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<tr>
<td>$M$</td>
<td>mass matrix</td>
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<tr>
<td>$P$</td>
<td>user-defined matrix</td>
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<tr>
<td>$Q$</td>
<td>LQR weights or p.d. matrix</td>
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<td></td>
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<tr>
<td>$R$</td>
<td>LQR weights</td>
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<td>$S$</td>
<td>sensitivity matrix</td>
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<td>$X$</td>
<td>state vector</td>
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<td></td>
</tr>
<tr>
<td>$\mathbb{R}$</td>
<td>real numbers</td>
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</table>
2.1 Introduction

In Chapter 1, we have divided controllers into two main categories: fixed and adaptive controllers. Fixed controllers are generally designed using known parametric properties, and the control gains remain fixed during the control stage. They can also be adapted to account for some uncertainties in the systems. It is the case for robust stable controllers ($H_\infty$), robust LQR (or $H_2$), among others. Adaptive parameters, as their name suggests, allow for some adaptation or variation throughout the control process. A special case of adaptive controller are intelligent controllers. Intelligent controllers are typically black-box representations that are constructed using adaptation or training rules. They are very useful when parametric properties are largely uncertain, or even unknown. This class of intelligent controllers will be our primary choice for the proposed controller, as our work focusses on systems with large parametric uncertainties.

The purpose of this chapter is to introduce a modified intelligent controller, tailored to semi-active control systems. It is only in the subsequent chapter that novel will describe the controller, a wavelet neural network (WNN) controller, after we introduce a new feature permitting the controller to adapt to nonstationary systems with limited measurements. Before explaining those features, a first overview of control theories is provided at the beginning of this current chapter. Section 2.2 reviews some types of fixed controllers (LQR, $H_\infty$, SMC), while Section 2.3 will be concerned by adaptive controllers (MRAC, Fuzzy, Neural Net). More attention will be given to sliding mode control (SMC) and neural nets, as they are the main features of the modified WNN, which will be presented in Section 2.4. Note that the WNN forms the basis of our new controller. Section 2.5 will conclude this chapter.

Before starting with the theory of fixed controllers, a short review of the some popular transfer function models is provided.

2.1.1 Transfer Function Models

A linear system can be written as \cite{113}:

$$y(t) = G(q)u(t) + H(q)e(t)$$ \tag{2.1}

with
CHAPTER 2. CONTROL ALGORITHMS FOR LARGE PARAMETRIC UNCERTAINTIES

\[ G(q) = \sum_{k=1}^{\infty} g(k)q^{-k} \]  \hspace{1cm} (2.2)

\[ H(q) = \sum_{k=1}^{\infty} h(k)q^{-k} \]

where \( y \) is the observation, \( e \) is the white noise, \( t \) is time, \( G \) and \( H \) are transfer functions, and \( q^{-1} \) is the time delay operator such that:

\[ q^{-k}y(t) = y(t - k\Delta t) \]  \hspace{1cm} (2.3)

The notation could easily be applied to MIMO systems, where \( G \) and \( H \) would be written as matrices, but we keep the scalar notation for simplicity. The linear system (2.1) can be written with fewer parameters. Ignore the white noise component of (2.1), and take:

\[ g(k) = a^{k-1} \]  \hspace{1cm} (2.4)

such that:

\[ G(q) = \sum_{k=1}^{\infty} a^{k-1}q^{-k} \]  \hspace{1cm} (2.5)

or, multiply by \( a/q \):

\[ \frac{a}{q}G(q) = \sum_{k=1}^{\infty} a^k q^{-k-1} \]

\[ = \sum_{k=2}^{\infty} a^{k-1}q^{-k} \]  \hspace{1cm} (2.6)

\[ = G(q) - \frac{1}{q} \]

and rearrange:
2.1. INTRODUCTION

\[
(1 - \frac{a}{q}) G(q) = \frac{1}{q}
\]

\[
\rightarrow G(q) = \frac{q^{-1}}{1 - aq^{-1}} = \frac{1}{q - a}
\]

(2.7)

to show that \( G(q) \) can be represented by only one pole using a rational function.

The objective is thus to represent \( G(q) \) and \( H(q) \) with less parameters, which can be done using a proper model structure for the transfer function. In this section, we review the principal ones: auto regressive with exogenous input (ARX), finite impulse response (FIR), moving average auto regressive with exogenous input (ARMAX), output error (OE), and state-space representation models.

Before we proceed, the reader might wonder why we are concerned with representation of linear systems, as we aim at designing a general controller applicable to general nonlinear dynamic systems. The reason is that we will treat nonlinearity as external forcing. We will assume at our system is primarily linear, and its nonlinear behavior, whether it is inherited by plastic deformation or nonlinear control devices, will be external time varying forces. The linear approximation models will be useful to determine control rules. As we will discuss later, they will be linear combination of nonlinear terms.

**ARX Model Structure**

ARX models represent the response of linear systems by an auto regression on the observation and a linear combination of the inputs. The transfer functions \( G(q) \) and \( H(q) \) are written:

\[
G(q) = \frac{B(q)}{A(q)}
\]

\[
H(q) = \frac{1}{A(q)}
\]

(2.8)

where:

\[
A(q) = 1 + a_1 q^{-1} + \ldots + a_n q^{-n_a}
\]

\[
B(q) = b_1 q^{-1} + \ldots + b_n q^{-n_b}
\]

(2.9)
Thus, the estimated observation can be written:

\[ \hat{y}(t) = -a_1 y(t-1) - \ldots - a_{n_a} y(t-n_a) + b_1 u(t-1) + \ldots + b_{n_b} u(t-n_b) + e(t) \]  \hspace{1cm} (2.10)

FIR Model Structure

FIR models are a special case of the ARX model structure where \( n_a = 0 \). Thus, the observation is written:

\[ \hat{y}(t) = B(q) u(t) + e(t) \]  \hspace{1cm} (2.11)

or:

\[ \hat{y}(t) = b_1 u(t-1) + \ldots + b_{n_b} u(t-n_b) + e(t) \]  \hspace{1cm} (2.12)

ARMAX Model Structure

ARMAX models include the structure of the ARX plus the delayed error. It can be written as:

\[ G(q) = \frac{B(q)}{A(q)} \]

\[ H(q) = \frac{D(q)}{A(q)} \]  \hspace{1cm} (2.13)

where:

\[ D(q) = 1 + d_1 q^{-1} + \ldots + d_{n_d} q^{-n_d} \]  \hspace{1cm} (2.14)

Thus, the estimated observation can be written:

\[ \hat{y}(t) = -a_1 y(t-1) - \ldots - a_{n_a} y(t-n_a) + b_1 u(t-1) + \ldots + b_{n_b} u(t-n_b) + e(t) + d_1 e(t-1) + \ldots + d_{n_d} e(t-n_d) \]  \hspace{1cm} (2.15)
OE Model Structure

The OE model is used for systems for which the only noise affecting the system is white noise. In other words, the noise dynamics is independent of the process dynamics, analogous to the Kalman Filter method. A simple OE representation is the Box-Jerkins model structure:

\[ G(q) = \frac{B(q)}{F(q)} \]
\[ H(q) = \frac{D(q)}{A(q)} \]  

where:

\[ F(q) = 1 + f_1 q^{-1} + \ldots + f_n q^{-n_f} \]

State-Space Model Structure

To define the state-space representation, we will use a notation slightly different than the one used to describe previous models, in order to stay consistent with traditional notation. Consider the equation of motion of a structure:

\[ M \ddot{x} + C \dot{x} + K x = -F u - M a_g - E w \]  

where \( x \in \mathbb{R}^{n \times 1} \) is the displacement vector, \( M \in \mathbb{R}^{n \times n}, C \in \mathbb{R}^{n \times n}, \) and \( K \in \mathbb{R}^{n \times n} \) are the mass, damping, and stiffness matrices respectively, \( F \in \mathbb{R}^{n \times a} \) is the actuator location matrix, \( E \in \mathbb{R}^{n \times 1} \) is a vector of ones, \( n \) is the number of states, \( a \) is the number of actuators, \( u \in \mathbb{R}^{a \times 1}, a_g \in \mathbb{R}^{1 \times 1}, \) and \( w \in \mathbb{R}^{n \times 1} \) in the wind excitation. Note that this is the same equation as (1.1), where the disturbance has been divided between wind and earthquake excitations.

We can rewrite (2.18) in the form:

\[ \ddot{x} = -M^{-1} (C \dot{x} + K x + F u + M a_g + E w) \]  

which can conveniently be represented in matrix notation:

\[ \dot{X} = AX + B_f u + B_g a_g + B_w w \]  

with:
CHAPTER 2. CONTROL ALGORITHMS FOR LARGE PARAMETRIC UNCERTAINTIES

\[
A = \begin{bmatrix} O & I \\ -M^{-1}K & -M^{-1}C \end{bmatrix} \quad X = \begin{bmatrix} x \\ \dot{x} \end{bmatrix}
\]

\[
B_u = \begin{bmatrix} O \\ -M^{-1}F \end{bmatrix} \quad B_g = \begin{bmatrix} O \\ -E \end{bmatrix} \quad B_w = \begin{bmatrix} O \\ -M^{-1}E \end{bmatrix}
\]

where \( I \in \mathbb{R}^{n \times n} \) is the identity matrix, and 0 are compatible zero matrices such that \( A \in \mathbb{R}^{2n \times 2n} \), \( B_u \in \mathbb{R}^{2n \times a} \), \( B_g \in \mathbb{R}^{2n \times 1} \), \( B_w \in \mathbb{R}^{n \times 1} \), \( X \in \mathbb{R}^{2n \times 1} \). Note that for simplicity, we will sometime use \( B \) to aggregate the representation of all inputs. The form (2.20) is termed the state-space representation.

2.2 Fixed Controllers

2.2.1 \( H_\infty \)-Based Controllers

As their name suggests, the objective of \( H_\infty \)-based controllers is to minimize the maximum norm of a system. Thus, the controller attempts at minimizing the maximum response of a controlled system, which is termed the sensitivity of a system, and is typically achieved in the frequency domain. Zames \([222]\) introduced the problem of minimizing the peak value of the sensitivity function \( S \) generally written:

\[
\|S\|_\infty = \max_{\omega \in \mathbb{R}} |S(j\omega)| \tag{2.21}
\]

where \( \omega \) is the frequency. The \( H_\infty \) controllers objective is to minimize (2.21) in function of disturbance, or system uncertainties, which is referred to robust control, or stability under perturbation. Consider Fig. 2.1, which consists of the Nyquist plot of the loop gain \( L_0 \). The gain is allowed to be perturbed to \( L \). The question is whether the system remains stable, which is guaranteed if the perturbed gain \( L \) does not encircle the point -1. Systems that can be perturbed and do not encircle the point -1 are termed stable systems. The sensitivity \( S \) is how much is left of possible disturbance before reaching instability. Systems that are robust and which sensitivity does not encircle the point -1 are termed robust stable. Remark that there is a difference between sensitivity and perturbations, where sensitivity is how much a system response is allowed to be under control, and perturbation is how much uncertainty is allowed in the controlled system. Fig. 2.2 illustrates the concept for a single-degree-of-freedom system, where \( \Omega \) is the natural frequency, and \( H \)
2.2. FIXED CONTROLLERS

Figure 2.1: Stability under perturbation (adapted from [94]).

is the amplitude of the transfer function. The plain blue line corresponds to the uncontrolled system, the red dot line corresponds to the controlled system where the gain has been designed with full parametric knowledge, and the black dash line corresponds to the controlled system allowing 20% perturbation of the mass. The system is stable under the red dot line, and the system is robust stable under the black dash line.

There are numerous applications of $H_\infty$ to civil structures. For instance, Wang et al. [198] applied robust control to civil structures with unstructured uncertainties. Wang et al. [199] extended the concept to structures with both parametric and unstructured uncertainties. Yang et al. [213] applied $H_\infty$ control to a 76-story benchmark structure subjected to wind, and to a benchmark bridge subjected to an earthquake. The authors compared two different norms: an energy bound and a peak bound. Wu et al. [206] proposed an $H_\infty$ control for the 76-story benchmark building equipped with an active mass driver (AMD) system. They used the AMD to identified structural response in the Laplace domain.

2.2.2 Linear Quadratic-Based Controllers

Similar to $H_\infty$-based controllers, LQR controllers are designed based on the minimization of a norm, the 2-norm in this case. They are also known as
CHAPTER 2. CONTROL ALGORITHMS FOR LARGE PARAMETRIC UNCERTAINITIES

\begin{figure}[h]
\centering
\includegraphics[width=0.5\textwidth]{figure2.2}
\caption{Stability and robustness, $H_\infty$ controller.}
\end{figure}

$H_2$ controllers. Typically, they have the following objective function $J$ to minimize for regulatory control:

\[ J = \frac{1}{2} \int_0^\infty x^T Q x + u^T R u \, dt \]  \hspace{1cm} (2.22)

where $x$ is the state vector, $u$ is the force input vector, and $Q$ and $R$ are the control weight matrices for the states and force inputs respectively. In contrast with $H_\infty$ controllers, the LQR control rules are designed in the time domain. The minimization of (2.22) will lead to a gain matrix $G$ that will define the feedback force $u = -G x$. In the state-space formulation, we can write:

\[ \dot{x} = Ax + Bu = (A - BG)x \]  \hspace{1cm} (2.23)

In other words, the gain matrix $G$ can be selected for pole placement of the state-space matrix $A$, which is achieved by minimizing (2.22). The idea of robustness from the previous section also extends to LQR controllers. The system can be stabilized using pole placement as in (2.23), where the equation is modified to include uncertainties.
2.2. FIXED CONTROLLERS

\[ \dot{x} = ((A \pm \Delta_A) - (B \pm \Delta_B)G)x \] \hspace{1cm} (2.24)

where \( \Delta \) represents the associated range of parametric uncertainties on \( A \) and \( B \). Thus, design of an LQR robust controller can simply be realized by stabilizing the worst case scenario. For instance, Fig. 2.3 illustrates a system (blue solid line) to be controlled using an LQR controller. The gains are designed based on the system parameters (red dot line). The same control rule is illustrated, but with a system which mass has been perturbed by 20% (black dash line). The area under the red dot line represents a stable system, while the area under the black dash line represents a robust stable system. For a more rigorous analytical discussion on robust LQR design and optimal design strategies, the reader is referred to [110]. One of the main advantages of LQR controllers is their applicability in the time domain. This is convenient to us, because the controller introduced in this manuscript is also constructed in the time domain. Thus, when performance comparisons with full parametric knowledge will be suited, we will often use an LQR controller.

![Figure 2.3: Stability and robustness, LQR controller.](image)

LQR controllers are the most widely used in control [127]. In adaptive systems, Jalili et al. [75] tuned their LQR control parameters with a genetic
algorithm (GA). Novak et al. [146] presented an adaptive LQR controller. Yang et al. [215] applied $H_2$ control in the same context as in [213]. In applications to civil engineering, Lin and Loh [111] used an LQR controller with limited measurements to control a floor isolation system equipped with MR dampers. Gu et al. [56] used an LQR controller with a Kalman filter for structural control. Loh and Chang [114] used an LQR controller with acceleration feedback for a 20-story benchmark control problem.

### 2.2.3 Lyapunov-Based Controllers

Lyapunov-based controllers are derived from the infamous Lyapunov stability theory. A system is said to be stable if, for any $R$, there exist a ball of radius $r$ which includes the initial condition which guarantees that the state will not leave $R$ at any time. Mathematically, we can write [171]:

\[
\forall R > 0, \exists r > 0, \|x(0)\| < r \Rightarrow \forall t \geq 0, \|x(t)\| < R \tag{2.25}
\]

The concept of Lyapunov stability can also be represented mathematically by a function that is always positive definite and which time derivative is at least negative semi-definite. Such function is termed a *Lyapunov function*, and is often represented by $V$. For instance, the function $e^{-t}$ is a Lyapunov function:

\[
V = e^{-t} \quad \dot{V} = -e^{-t} \tag{2.26}
\]

where $V > 0$ and $\dot{V} < 0$. Fig. 4.24 illustrates the concept of Lyapunov stability. In Fig. 2.4a, a ball is in a bowl. If it gets perturbed, it comes back at its original position and at rest provided that there is friction. Fig. 2.4b shows a system that is marginally stable. When the ball is perturbed, it comes at rest provided that there is friction, but not at its original position. Fig. 2.4c shows an unstable system, where a perturbation results in the ball going to infinity.

Intuitively, if we can always extract energy from a system, the system will come at rest at some point. For this reason, an energy function is often taken as the Lyapunov function. To give an example, we study the stability of a civil structure. We take $V$ and its derivative to be:
2.2. FIXED CONTROLLERS

Figure 2.4: Illustration of Lyapunov stability: a) stable system; b) marginally stable system; and c) unstable system.

\[ V = \frac{1}{2} x^T P x \]
\[ \dot{V} = \frac{1}{2} (\dot{x}^T P x + x^T \dot{P} x) \]
\[ = \frac{1}{2} \left( (Ax + Bu)^T P x + x^T P (Ax + Bu) \right) \tag{2.27} \]
\[ = \frac{1}{2} \left( x^T A^T P x + x^T P A x \right) + u^T B^T P x \]
\[ = \frac{1}{2} x^T (A^T P + PA) x + u^T B^T P x \]

where \( P \) is symmetric and positive-definite. Consider the case of an uncontrolled structure (\( u \equiv 0 \)). Any \( P > 0 \) satisfies \( V > 0 \) and \( \dot{V} < 0 \) as, for civil structures, \( A < 0 \) assuming some damping (\( x^T P x > 0 \) for \( P > 0 \), and \( x^T (A^T P + PA) x < 0 \) since \( (A^T P + PA) < 0 \) as \( PA < 0 \)). Thus, civil structures are inherently stable. Now, taking a negative feedback control rule (\( u = -Gx \)), (2.27) becomes:
CHAPTER 2. CONTROL ALGORITHMS FOR LARGE PARAMETRIC UNCERTAINTIES

\[
\dot{V} = \frac{1}{2} x^T (A^T P + PA)x - x^T (G^T B^T P)x
\]  

where one has to select \( G^T B^T \geq 0 \) to satisfy \( \dot{V} < 0 \). It is easy to verify that any \( G \) with all positive elements satisfies this requirement. In other words, adding equivalent stiffness and damping stabilizes the system. Note that the dynamics of semi-active devices are typically equivalent to positive semi-definite gain matrices \( G \geq 0 \).

Sliding Mode Control

In this subsection, we discuss SMC using a Lyapunov-based approach \[170\]. Unless specified otherwise, a scalar notation is used for simplicity, but the theory can easily be extended to matrix forms.

SMC aims at bringing the controlled system on a surface of known dynamics on which the error will exponentially converge to zero. Let the tracking error \( e \) of a state \( x \) be written \( e = x - x_d \) where \( x_d \) denotes the desired state (\( x_d \equiv 0 \) for regulatory problems). A sliding surface \( s \) is defined as:

\[
s(x, t) = \left( \frac{d}{dt} + \lambda \right)^{n-1} e
\]

where \( n \) is the order of the controlled system dynamics, and \( \lambda \) represents a control weight and is a strictly positive constant. In the case of a civil structure, (2.29) becomes:

\[
s(x, t) = \dot{e} + \lambda e
\]

Noting that (2.30) is stable for the manifold \( s = 0 \), we seek at bringing the system on such manifold, and ensuring that it remains on the surface for all \( t > 0 \) by designing an appropriate control law. The control law can be designed using a Lyapunov-based approach. Consider the following Lyapunov function based on surface error:

\[
V = \frac{1}{2} s^2
\]

\[
\dot{V} = ss
\]

62
2.2. FIXED CONTROLLERS

The problem could be reduced to finding a control input $u$ such that:

$$s \dot{s} \leq -\eta |s|$$  \hspace{1cm} (2.32)$$

where for $\eta$ being strictly positive, $\dot{V}$ in (2.31) will be negative definite. Thus, $s$ will converge to its solution $s = 0$, or:

$$\left( \frac{d}{dt} + \lambda \right)^{n-1} e = 0$$  \hspace{1cm} (2.33)$$

It can be shown that the sliding surface $s$ will be reached in a finite period of time, and that error converges exponentially to 0 once the system is on the sliding surface. Fig. 2.5 graphically represents the concept of SMC.

A controller designed to satisfy (2.32) will be discontinuous as the control force will abruptly change sign with the sliding error sign. This may lead to chattering, which causes unnecessarily high control forces and a possible excitation of the neglected high frequencies. Fig. 2.6 graphically represents the chattering phenomenon.

To reduce or eliminate chattering, the discontinuity in the control law must be transformed to let the sign transition be smooth and continuous. For instance, the dynamics of the transition of the control force sign can be enforced within a boundary layer. In this case, the absolute operator in (2.32) can be replaced by a saturation function $sat$:

$$s \dot{s} \leq -\eta \cdot sat \left( \frac{s}{\phi} \right) s$$  \hspace{1cm} (2.34)$$
Lyapunov-based controllers have been widely applied to control of civil structures. For instance, Adhikari and Yamaguchi [4] applied an SMC for control of an active TMD, where wind forces were estimated. Wu and Yang [207] applied a modified SMC with a Kalman-Bucy filter to a wind-excited benchmark problem. Ha et al. [59] used a Lyapunov-based controller to mitigate seismic response of a structure equipped with MR dampers.

### 2.3 Adaptive Controllers

Adaptive control is generally used for uncertain systems, whether the uncertainties are parametric or non-parametric. For example, consider a mechanical arm lifting an object with an unknown mass. We would not be able to project the arm into a given trajectory without any adaptive scheme, as we do not know the dynamics of the system once the arm grabs the mass. There are two main way of approaching that control problem. First, we can lift the mass, try different trajectories, and identify the new dynamic properties. This is called *indirect control*, as we conduct system identification for controlling the plant. Methods associated with indirect control include Model-Reference Adaptive Controllers (MRAC), and are typically used for *tracking* problems. The second way is to come up with a control rule, and adapt the control rule until we achieved our desired state. This is called *direct control*. Methods associated with direct control include Self-Tuning Controllers (STC), and are typically used for *regulatory* problems. Tracking control problems consist of bringing a system into a given trajectory, while regulatory control problems
are concerned with bringing the system at rest. Civil engineering control objectives, vibration mitigation for example, are typically regulatory. Tracking objectives are more rare, but we can find some applications in retractable roofs and drawbridges.

In this section, we first introduce the main differences between MRAC and STC. Subsequently, we will introduce a special type of adaptive controllers: intelligent controllers. We want to remind the reader here that we called intelligent controllers *adaptive* because of their capacity to be trained, whether it is online or offline, sequentially or by batch.

### 2.3.1 MRAC & STC

MRAC and STC are adaptive control schemes, where the controller parameters are adapted until the control objective is attained. The MRAC are qualified as indirect approaches, while, conversely, STC are qualified as direct approaches. Fig. 2.7 schematizes their concept. MRAC use a reference model with a similar dynamics than the controlled structure. The objective is to adapt the controller until both systems’ responses are synchronized. STC use a model of the controlled structure on which the controller is based. The model is adapted until the system output objective is attained. Note that the controller/model can be integrated in the form of a direct inverse controller.

**MRAC**

As we have seen in Fig. 2.7a, MRAC comprise a controlled plant, an estimated plant, and a reference model:

\[
\begin{align*}
\ddot{m} \ddot{x} + c \dot{x} + kx &= u \\
\ddot{m} \dddot{x} + \ddot{c} \ddot{x} + \dot{k}x &= u \\
m_m \dddot{x}_m + c_m \dot{x}_m + k_m x_m &= r
\end{align*}
\]

where the *hat* denotes estimations, subscripts *m* denotes the reference model, and *r* is the desired trajectory. We select a control law in the form of:

\[
u = \ddot{m}(\dddot{x}_m - \lambda \dot{e}) - \xi(\dot{e} + \lambda e) + \ddot{c} \ddot{x} + \dot{k}x
\]

and substitute in (2.35) to obtain:
CHAPTER 2. CONTROL ALGORITHMS FOR LARGE PARAMETRIC UNCERTAINTIES

Figure 2.7: Schematic representation of a) MRAC; and b) STC.

\[ m\ddot{x} - \hat{m}(\dddot{x}_m - \lambda \dot{e}) + \xi(\dot{e} + \lambda e) + (c - \hat{c})\ddot{x} + (k - \hat{k})x = 0 \] \hspace{1cm} (2.37)

Noting that for known parameters the error in (2.37) converges to zero, we need to select the appropriate adaptation laws in order to obtain:

\[ \lim_{t \to \infty} |m - \hat{m}| = 0 \]
\[ \lim_{t \to \infty} |c - \hat{c}| = 0 \]
\[ \lim_{t \to \infty} |k - \hat{k}| = 0 \] \hspace{1cm} (2.38)
The following adaptation laws:

\[
\begin{align*}
\dot{\hat{m}} &= -\gamma_s (\ddot{x}_m - \lambda \dot{e}) \\
\dot{\hat{c}} &= -\gamma_s \dot{x} \\
\dot{\hat{k}} &= -\gamma_s x
\end{align*}
\]  

(2.39)

can be shown to satisfy (2.38).

**Example: Application to a Semi-Active System**

Consider the case of a structure equipped with a semi-active damper. Assume that the reference trajectory is partly achievable via damping, thus of smaller magnitude than the external excitation. The governing equation of a single degree-of-freedom system semi-actively controlled between the base and the mass is written:

\[
m \ddot{x} + c \dot{x} + kx = u + d
\]  

(2.40)

where \( u \) is the semi-active force, and \( d \) is a measurable external disturbance. The control law (2.36) is modified:

\[
u_{\text{req}} = \hat{m}(\ddot{x}_m - \lambda \dot{e}) - \xi (\dot{e} + \lambda e) + \hat{c} \dot{x} + \hat{k}x - \tilde{u}
\]  

(2.41)

where \( u_{\text{req}} \) is the required force. Because of the semi-active nature of the control device, the required force \( u_{\text{req}} \) is not always reachable. The error \( \tilde{u} \) is defined as the error between \( u_{\text{req}} \) and the actual damping force \( u_{\text{act}} \). Equation 2.37 can be rewritten:

\[
m \dot{s} + \xi s = \hat{m}(\ddot{x}_m - \lambda \dot{e}) + \hat{c} \dot{x} + \hat{k}x - \tilde{u}
\]  

(2.42)

Thus, if all parameters were known, (2.42) would become:

\[
m \dot{s} + \xi s + \tilde{u} = 0
\]  

(2.43)

with its solution:

\[
s(t) = e^{(-\xi/m)t} - \tilde{u}/\xi
\]  

(2.44)

where \( s \to -\tilde{u}/\xi \) at \( t \to \infty \). The error is assumed to be negligible for large \( \xi \) and small \( \bar{f} \).
CHAPTER 2. CONTROL ALGORITHMS FOR LARGE PARAMETRIC UNCERTAINTIES

Take the system identification problem of the following unknown SDOF system:

\[ m = 100 \text{kg}; \quad c = 10 \text{Ns/m}; \quad k = 80 \text{N/m} \] \hspace{1cm} (2.45)

The reference model:

\[ m_m = 120 \text{kg}; \quad c_m = 64 \text{Ns/m}; \quad k_m = 12 \text{N/m} \] \hspace{1cm} (2.46)

is used for the simulation with an harmonic reference excitation \( r = \sin 8t \text{ m} \), and the MRAC parameters set to \( \lambda = 100, \xi = 500, \gamma = 50 \). The disturbance consists of three harmonic excitations of frequency 1, 2, and 4 rad/s, and amplitude 10, 8, and 6 m respectively. An unmeasurable Gaussian error of center 0 and magnitude 5 m has been added to the disturbance. Fig. 2.8 shows the convergence of the estimated parameters over 15 seconds of simulation. After 15 seconds, the final parameters are \( \hat{m} = 101.5 \text{ kg}, \hat{c} = 12.19 \text{ Ns/m}, \) and \( \hat{k} = 80.0 \text{ N/m} \), which represents estimation errors of 1.5%, 22%, and 0.0% respectively. The large error on the damping can be explained by the low contribution of the parameter to the system dynamics.

STC

We will spend more time describing the STC, as their concept is quite general and many adaptive methods are in fact STC. In addition, our proposed controller is a form of STC, and the method will be described in depth later in this chapter.

STC include classes of mathematical or non-mathematical models used for selecting controller parameters. Mathematical representations include recursive least-square, recursive extended least square, recursive instrumental variables, recursive maximum likelihood, and stochastic approximation [172]. Some of those methods typically require high computation time and are best suited for batch training. Neural networks are generally qualified as non-mathematical model because they are principally used in machine learning for pattern classification. However, we use here neural networks as a function representation of the system based on human neurons. The outputs of the neural nets are a linear combination of linear or nonlinear functions. Consequently, we leave neural networks in the family of mathematical representations.

Non-mathematical models include genetic algorithms, fuzzy logic and classification neural networks. They are often refer as intelligent controllers.
because of their ability to optimize controllers based on machine learning techniques. Intelligent controller advantages include: 1) tolerance to model uncertainties; 2) less prior knowledge required; 3) capacity to handle non-linearity; and 4) possibility of quick convergence \[77\]. Genetic algorithms have shown good performance at system identification and control, but they generally require a very long computation time and have a high possibility to end up in a local minima \[16\].

In what immediately follows, we describe the special set of intelligent controllers, with an emphasis on neurocontrollers.

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Figure 2.8: Convergence of the estimated parameters: a) the mass $\hat{m}$; b) the damping $\hat{c}$; and c) the stiffness $\hat{k}$.
CHAPTER 2. CONTROL ALGORITHMS FOR LARGE PARAMETRIC UNCERTAINTIES

2.3.2 Intelligent Controllers

Intelligent controllers are a special class of adaptive controllers. They are characterized by their capacity to create a function representation based on training from input-output data sets. This representation can be achieved using numerous system identification tools, such as fuzzy logic, neural networks (including radial basis function and wavelet networks), polynomial models, and rational models [159, 7]. For instance, as we will see later, a function $f$ can be approximated in term of a linear combination of functions $\phi$:

$$ f(x(k), u(k)) = \sum_{i=1}^{h} \gamma_i \phi_i(x(k), u(k)) $$  \hspace{1cm} (2.47)

where $h$ is the number of nodes in the network, and $\gamma$ are the nodal weights. This representation in linear-in-the-parameters and is designed or trained based on input-output data sets.

This subsection provides a short description of the two most popular types of representations in structural control: fuzzy logic and neural networks. We will focus on neural networks, as they constitute the basis of the proposed controller.

Fuzzy Logic

Fuzzy logic, as its name suggests, is a control rule derived from the mathematics of sets. It has been introduced by Zadeh in 1973 [221] to characterize numerical problems using a logistic approach. In fuzzy logic, the space is separated into sets that are not necessarily mutually exclusive, and a particular event is classified in these sets with degrees of membership. Based on the degree of membership, actions are taken. Fig. 2.9 is a simple representation of a fuzzy set. Here, control actions are separated in five sets, from very small (VS) to very large (VL), and are applied according to the degree of membership of the excitation (from low to very high). Note that an excitation can belong to multiple sets, and the action can be a weighted sum of the degrees of membership, which allows a smooth transition between sets of action.

Major drawbacks of fuzzy logic include lack of systematic design or stability analysis, mathematical intractability, and usually worst performance than other control schemes [72]. In applications of fuzzy logic to control, Schurter and Rosche [163] applied a fuzzy controller based on acceleration feedback.
2.3. ADAPTIVE CONTROLLERS

Figure 2.9: Example of a fuzzy set. VS = very small; S = small; M = moderate; L = large; VL = very large.


Neural Networks

Neural networks (NNs) are inspired by biology, mimicking the human neurons. Fig. 2.10 shows a simplified schematic for the analogy of NNs with biological neurons. A biological neuron can send a signal to other neurons only if the sum of the excitation received from its dendrites is above a certain threshold.
If it does send a signal, the neuron is said to fire. The signal then proceeds from the axon to dendrites of adjacent neurons through synapses [160].

An artificial node is based on that biological representation. The input links (dendrites) are multiplied by connection weights and added up together with a bias weight (the activation threshold) as an input function. The artificial neuron will process the information with respect to an activation function (cell body) and generate an output that will be directed to other neurons (axon) [203], as illustrated in Fig. 2.11.

Artificial neurons are represented in the form of networks. The network is built in order to receive inputs, process these inputs internally and finally generate outputs, thus a black-box or input-output system.

NNs were originally composed of a single layer. In the 1980’s, intensive research has resulted in the discovery of feed-forward multilayer NNs [12].
Feed-forward multilayer NNs are composed of several hidden layers comprised between an input and an output layer. They are called feed-forward because the inputs are processed forwardly until they become outputs. There exist, however, many kinds of NNs, among which the recurrent networks, where the outputs are processed back into the system. These have recently attracted significant attention in research for their ability to handle time series data. A complete description of the different types of neural networks is given in [60].

The challenge in using NNs is in the ability to choose consistent activation functions, to design a correct number of nodes (neurons) and layers, and to assign proper connection weights. All of these are, of course, interconnected.

Activation functions are traditionally the sigmoid function $1/(1 + e^{-bt})$, where $b$ is a positive constant, or a simple linear function. The sigmoid function is generally preferred over a step function because it is smooth and does not necessitate an if function. In the case of the sigmoid function, the bias weight represents the threshold as its purpose is to shift the function, setting the value above which the node will fire. The linear function will allow the output to match the desired order of response. There exists several other useful activation functions. The reader is directed to [60] for a more extensive listing.

Gaussian radial functions have been developed to replace traditional activation functions [161]. Such neural networks comprise several advantages compared to traditional neural networks, among which are better approximation, convergence speed, optimality in solution and excellent localization [181]. Those networks can also be trained more quickly than most other neural network techniques to model nonlinear systems by estimating in the function space [161, 83, 69]. Zhang and Beneviste [225] introduced the concept of wavelet neural networks for system identification, and showed the wavelet capability to achieve universal approximation. Cannon & Slotine [27] proposed to use wavelet neural network for control. Hung et al. [71] applied a wavelet neurocontroller for active control of a civil structure. Their neural net used batch training. For the proposed neurocontroller in the upcoming section, wavelet functions have been selected over Gaussian radial functions for their better space and frequency localization property. Unlike Gaussian functions, their locality in spatial frequency allows adaptive tuning of the function approximation with respect to variations of the local spatial bandwidth of the controller [27]. Thus, the training is quicker due to a more efficient representation.
CHAPTER 2. CONTROL ALGORITHMS FOR LARGE 
PARAMETRIC UNCERTAINTIES 

2.4 WNN for Semi-Active Control 

The wavelet neurocontroller presented in this section is developed for control of 
dynamic systems with unknown dynamic parameters. Additionally, it is 
adapted for the case of control devices having uncertain force output, which 
is the main contribution of this chapter. The force output error $\tilde{u}$ from those 
devices can be written:

$$\tilde{u} = u - u_{act}$$ \hspace{1cm} (2.48) 

where $u$ is the required force output from the algorithm and $u_{act}$ is the 
actual force output from the device. Example of devices having such force 
uncertainties are low capacity actuators, semi-active systems, and some hybrid 
systems.

Some efforts have been made in the field of structural control to achieve 
adaptive control with semi-active devices. Hidaka et al. [64] proposed 
an adaptive neural network controller for a three-story structure equipped 
with electrorheological dampers. The control strategy was composed of a 
predictive neural net and a controller neural net. The training scheme, 
however, necessitated the sets of input-output data from various types of 
excitation to apply batch training. Morishian et al. [133] proposed a neural 
network to control a three-story structure equipped with an MR damper. 
Similar to [64], the strategy required batch training.

In work done for control using sequential learning, Zhou et al. [229] used 
adaptive fuzzy control for a nonlinear base isolation system equipped with an 
MR damper. Their controller adapted sequentially. Lee et al. [100] developed 
a semi active neurocontroller for base-isolation control with an MR damper, 
where the neural network was updated using a cost function and sensitivity 
evaluation. In their work, the cost function included the error on states, the 
control signal, and weighting matrices. Using weighting parameters, however, 
necessitates prior simulation or testing for their evaluation. Lee et al. [81] 
achieved an adaptive modal neurocontroller for a structure equipped with an 
MR damper. This extension of [100] used a Kalman filter to estimate 
modal states, and controlled the structure based on those states using the 
neurocontroller. Suresh et al. [181] proposed an adaptive mapping scheme that 
uses Gaussian radial functions to control base-isolation of nonlinear buildings 
equipped with an actuator. The proposed mapping has the advantage of 
a structure to self-learn during an event, while having the potential to use
limited state measurements. We have presented a neurocontroller in [95]. The neural net is an inverse controller whose nodes sequentially adapt to achieve optimal control. The most significant contribution of the paper is the modification of the algorithm presented in Suresh et al. [181] to map the behavior of a civil structure equipped with semi-active devices, where adaptation is realized using a sliding controller and adaptive learning rates. A modified version of the controller [99, 97] includes an enhanced robustness in the adaptation laws and uses wavelets instead of Gaussian radial functions for a better function localization.

Despite the fact that research in structural control geared towards adaptive control of semi-active devices seems to be limited, more has been done for car suspension mechanisms. Song et al. [173] proposed an adaptive controller for such mechanism. The controlled system was identified sequentially, and also included an adaptive controller in parallel. The research claimed to be the first to address the adaptive control of MR dampers with immeasurable nonstationary vibration sources, an applicability concern in the context of car suspension. System identification was achieved on a single degree-of-freedom system using a recursive least square (RLS) algorithm. However, the RLS algorithm tends to be less effective for systems with multiple degrees-of-freedom.

We detail the proposed neurocontroller in the subsequent subsections.

### 2.4.1 Network Architecture

The proposed neurocontroller is a direct inverse controller designed to output forces based on the observations of the state inputs and control forces:

\[
  u_d(t) = f((y(t), y(t - \Delta t), ..., y(t - d\Delta t), u(t - 1), u(t - 1 - \Delta t), ..., u(t - 1 - d\Delta t))
\]

where \(u_d\) denotes the desired force, \(y\) the state observation, \(u\) the input, \(f\) the hidden layer function linear in the parameters, \(\Delta t\) a time step, and \(d\) a dimension. Thus, the neural network has an ARMAX model structure, as depicted in Fig. 2.12. The input parameter selection will be discussed later. The hidden layer functions are composed of radial wavelets.

This hidden layer is capable of self-organization mapping, as well as self-adaptation. Self-organization mapping, developed by Kohonen [91], refers to
the internal organization of nodes: nodes are added if the Euclidian distance of the input with respect to any existing node is larger than a certain threshold, and nodes can be pruned if judged unnecessary. Self-adaptation of nodes refers to the strategy of adapting nodal parameters.

The utilization of a self-adapting scheme arises from the choice of using sequential training rather than batch training, as batch training is difficult to achieve for large-scale systems because of the unavailability of input-output data sets. Sequential training consists of adapting the neurocontroller after each time step based on its performance. This is equivalent to changing the weight of the functions, along with the bandwidths and locations of wavelet functions. There exist several adaptation algorithms for neural nets, including: back-propagation (BP), resource allocating network (RAN) [153], RAN with extended Kalman filtering [83], minimal RAN [218], and recursive least-square. Among those methods, the BP algorithms is superior in its computational simplicity [18]. Considering real-time control, the applicability of the neural controller requires computational simplicity and minimal data storage in order to avoid time delay. Noting that the BP scheme has slow convergence, time-varying learning rates are use to provide the neurocontroller with accelerated convergence for high magnitude dynamic responses. Training is slowed when the performance approaches a prescribed threshold, and stopped when the
threshold is reached.

The neurocontroller maps the force output with respect to states. It results that the number of outputs corresponds to the number of actuators. The choice of state input is more involved. Prior knowledge of the system dynamics can improve the performance of the controller by specifying the types of inputs and the size of the lag space. This lag space has to be large enough to encompass the dynamics that properly describes the system, and multivariate inputs need to be appropriately scaled to improve the algorithm robustness and convergence speed [145]. Input selection is the central focus of the next chapter. Consequently, the choice of the input vector for the proposed neurocontroller will not be discussed in this current chapter.

As aforementioned, the main contribution of this chapter is the design of an adaptive controller specialized for control devices with uncertain force output, such as semi-active devices. In their case, the force uncertainty arises from the incapacity to add energy to a system. The strategy is to let the neurocontroller adapt when it is in a desired control region $C_d$, a region where the uncertainty on the control device force output is minimum. This region is comprised within the general set $C$. When the system is outside $C_d$, the objective is to try bringing the system back in the desired region. This is achieved using a sliding controller. A third region, located at the boundary of $C_d$, is incorporated and acts as the transition region $C_t$ to ensure a smooth transition between both control rules: $C \supseteq C_t \supseteq C_d$. The relationship is depicted in Fig. 2.13 for the case of an MR damper.

Fig. 2.14 shows a representation of the controller. The structure is excited by an external signal and the control device. Its dynamic states, as well as the damping forces, are fed in the adaptive neurocontroller. The neurocontroller outputs are fed in the sliding controller that adjusts the force based on the force reachability regions mentioned above. A voltage is then sent to the semi-active device based on the required force using a saturation rule, which will be defined later.

The next subsections describe the wavelet functions, followed by the self-organizing and the self-adaptive features, and a discussion on the choice of inputs, time delay, measurement errors, and the control strategies.

### 2.4.2 Wavelet Functions

Wavelets are dictionary of functions that can be used to decompose a signal. Waveforms $\phi_x$ of unit norm form a time-frequency dictionary $\mathcal{D} = \{\phi_x\}$. A
CHAPTER 2. CONTROL ALGORITHMS FOR LARGE PARAMETRIC UNCERTAINITIES

Figure 2.13: Illustration of controlled regions $C$, $C_t$, and $C_d$ for a 1 kN magnetorheological damper.

Figure 2.14: Block diagram of the closed-loop control system.
2.4. WNN FOR SEMI-ACTIVE CONTROL

Mother wavelet is a wavelet of zero average that can be translated by a scale parameter $\mu$ and dilated by a scale parameter $\sigma$ to obtain daughter wavelets that will form the dictionary $\mathcal{D}$ [122]:

$$\int_{-\infty}^{+\infty} \phi(t) \, dt = 0$$ \hspace{1cm} (2.50)

$$\mathcal{D} = \left\{ \phi_{\mu,\sigma}(t) = \frac{1}{\sqrt{\sigma}} \phi\left(\frac{t - \mu}{\sigma}\right) \right\}$$

The continuous wavelet transform of a function $f$ is written:

$$\mathcal{W}f(\mu, \sigma) = \langle f, \phi_{\mu,\sigma} \rangle = \int_{-\infty}^{+\infty} f(t) \frac{1}{\sqrt{\sigma}} \phi\left(\frac{t - \mu}{\sigma}\right) \, dt$$ \hspace{1cm} (2.51)

As aforementioned, the objective here is to construct the ARMAX representation $\tilde{f}$ of the control function $f$:

$$u(t) = f(y, u, t)$$ \hspace{1cm} (2.52)

To find the representation, we decompose $f$ in wavelets. Particularly, we will use Mexican hat wavelets $\phi$ of the form:

$$\phi(\nu) = \left(1 - \frac{||\nu - \mu||^2}{\sigma^2}\right) e^{-\frac{||\nu - \mu||^2}{2\sigma^2}}$$ \hspace{1cm} (2.53)

where $\nu$ is now used as the general input vector, $\mu$ and $\sigma$ are the center and bandwidth of the function respectively. In other words, the controller will be a single layer neural net using these wavelets as activation functions. Fig. 2.15 shows a 3-dimensional mexican hat wavelet, along with some of its variations.

The output of the representation, the desired force $u_d$, can be written:

$$u_{d,j}(\nu) = \sum_{i=1}^{h} \gamma_{i,j}\phi_i(\nu) = \gamma_j^T \phi(\nu)$$ \hspace{1cm} (2.54)

where $\gamma_{i,j}$ is the nodal weight $i$ associated with the output $j$, $h$ is the number of nodes in the hidden layer. Fig. 2.16 shows a single-layer feed-forward wavelet neural network.

For simplicity, the neurocontroller is specialized for a single device. The subscript $j$ will be dropped. Note that this formulation holds for the case of decentralized controllers, which are used for the main simulations (Chapter 5).
CHAPTER 2. CONTROL ALGORITHMS FOR LARGE PARAMETRIC UNCERTAINTIES

2.4.3 Self-Organizing Mapping

The self-organizing feature of the neurocontroller consists of adding a node when the Euclidean distance of a new output to the closest node is farther than the threshold $\eta$. The network also has the capacity to prune nodes when their weights are found to be under a predefined ratio of the largest weight for several consecutive time steps. New nodes are added at the center of the new input, with the target weight $\gamma_i$. Existing nodes are pruned if their weight falls below the threshold $\lambda$. The choice of $\gamma_i$ depends on $\lambda$. A function $f$ can be mapped as a summation of wavelets by the frame operator $\mathcal{F}$:

$$\mathcal{F}f = \langle f, \phi_i \rangle = \Sigma_{i=1}^{h} \phi_i f$$ \hfill (2.55)

Figure 2.15: 2-dimensional Mexican Hat wavelet. a) Original wavelet; b) bandwidth of the wavelet scaled up by a factor of 2; and c) translated wavelet.
where \( h \) represents the number of wavelet functions. Note that in the case of semi-active control, the function \( f \) is bounded, as civil structures equipped with such devices are inherently stable. The adjoint operator \( \mathcal{F}^* \) is written:

\[
\langle \mathcal{F}^* \gamma, f \rangle = \langle \gamma, \mathcal{F} f \rangle = \sum_{i=1}^{h} \gamma_i \langle f, \phi_i \rangle
\]

so that:

\[
\mathcal{F}^* \mathcal{F} f = \sum_{i=1}^{h} \langle f, \phi_i \rangle \phi_i
\]

Therefore, a family of wavelets \( \phi_i \) can be written in terms of a family of wavelets \( \tilde{\phi}_i \) with zero mean:

\[
\tilde{\phi}_i = (\mathcal{F}^* \mathcal{F})^{-1} \phi_i
\]

where the set \( \tilde{\phi}_i \) is termed dual frame. Hence, the function \( f \) can be exactly reconstructed using coefficients:

\[
\gamma_i = \langle f, \tilde{\phi}_i \rangle
\]
CHAPTER 2. CONTROL ALGORITHMS FOR LARGE PARAMETRIC UNCERTAINTIES

Cannon and Slotine [27] show that, in order to prevent the addition of a node with an unrealistic weight that would result from a point sitting far from the existing function, the bound on $\gamma_i$ must be taken as:

$$|\gamma_i|_{max} = \gamma_0^{-d|\sigma|/2} |f|_{max} |\tilde{\phi}|_{max}$$  \hspace{1cm} (2.60)

where $\gamma_0$ is a scale parameter, $d$ is the dimension of the separable wavelet families with scale $\gamma_0$, $f$ is the bound on the estimated function and is equal to the bound on the control force $u_b$, and $|\tilde{\sigma}|_{max}$ is equal to the volume of the set $G_t$ in the case of mexican hat wavelets. The scale parameter $\gamma_0$ is taken from the dual frame family of radial wavelets that are written:

$$\tilde{\phi}_{i,(\sigma,\mu)} = \gamma_0^{-d|\sigma|/2} \phi_{i,(0,\mu)}(\gamma_0^{-d|\sigma|} \nu)$$  \hspace{1cm} (2.61)

where the subscript $(\sigma,\mu)$ denotes the scale $\sigma$ of the dual set $\tilde{\phi}$ centered at $\mu$, such that $\tilde{\phi}_{i,(0,\mu)}$ is a family of non-dilated wavelets centered at $\mu$. Taking the minimum bound $\lambda$ on the weights, it results that the bandwidth of the nodes from (2.60) is given by the expression:

$$\sigma = \frac{2}{d \log \alpha_0} \log \left( \frac{|u_b| C_t}{\gamma_i} \right) \leq \frac{2}{d \log \alpha_0} \log \left( \frac{|u_b| C_t}{\lambda} \right)$$  \hspace{1cm} (2.62)

From (2.62), it can be observed that reducing $\lambda$ increases the approximation capability of the neural network.

The target nodal weight $\bar{\gamma}_i$ of a newly added node $i$ is approximated using a weighted sum of the error. To enhance stability, a smooth interpolation is incorporated when nodes are added:

$$\dot{\bar{\gamma}}_i = \begin{cases} \dot{\gamma}_i & \text{if } |\gamma_i| \geq |\bar{\gamma}_i| \\ m_c(t) \gamma_i & \text{if } |\gamma_i| < |\bar{\gamma}_i| \end{cases}$$  \hspace{1cm} (2.63)

where $\dot{\gamma}$ is the parameter evolution according to the self adaptation rules described in the next subsection, and $m_c(t)$ is the smooth transition function infinitely differentiable and taken as the sigmoid function:

$$m_c(t) = \frac{1}{1 + e^{-bt}}$$  \hspace{1cm} (2.64)

with $b$ being a positive constant.
2.4. WNN FOR SEMI-ACTIVE CONTROL

2.4.4 Self-Adapting Feature

The adaptive rules of the neurocontroller are derived using Lyapunov stability to ensure robustness. Based on (2.54), the optimal mapping of control-input/state-output of the system equipped with a single semi-active damper can be expressed as:

$$u_d = \gamma^T \phi$$

(2.65)

where $u_d$ is the desired (optimal) control force. The control law used herein is taken as:

$$u(t) = (1 - m_c) (u_n - k \cdot \text{sat} \left( \frac{s}{\Phi} \right)) + m_c u_{sl}$$

$$= (1 - m_c) (u_n - k \cdot \text{sat} \left( \frac{s}{\Phi} \right)) - m_c u_{max} \text{sat} \left( \frac{s}{\Phi} \right)$$

(2.66)

where $u_n = \hat{\gamma}^T \hat{\phi}$ is the force output from the neurocontroller, the hat denotes estimated values, $u_{sl} = -u_{max}\text{sat}(s/\Phi)$ is the sliding component using the saturation function sat to bring the system back in subspace $C_d$, $k$ is a constant, $\phi$ is a scaling parameter for the sliding surface, and $m_c$ represents the control weight and is dependent on which subspace the system is located. Those terms will be mathematically defined later. The sliding surface $s$ is taken as:

$$s = Pe = 0$$

$$\dot{s} = P\dot{e} = 0$$

(2.67)

where $e$ is the error defined as the difference between the state $X$ and the desired state $X_d$, and $P$ is a user-defined vector. The selection of $P$ will be discussed later.

Using (2.65), (2.66), the equation of motion of civil structure in the state-space representation recalled here for convenience:

$$\dot{X} = AX + B_u u + B_g a_g + B_w w$$

(2.68)

and substituting $\tilde{u}$, the dynamics of the controlled state error can be written as:
\[ \dot{e} = \dot{X} - \dot{X}_d \]
\[ = Ae + B(u_{act} - u_d + \epsilon) \]
\[ = Ae + B \left( (1 - m_c) \left( \hat{\gamma}^T \hat{\phi} - k \cdot \text{sat} \left( \frac{s}{\Phi} \right) \right) + m_c u_{sl} - \gamma^T \hat{\phi} - \bar{u} + \epsilon \right) \]
(2.69)

where the subscript \( d \) denotes the desired states, and \( \epsilon \) is the estimation error.

Note that the unknown external loadings \( a \) and \( w \) were in both right hand side terms of (2.69), thus canceled out.

To derive the adaptation rules, consider the following Lyapunov candidate using the sliding controller [170]:
\[ V = \frac{1}{2} \left[ s^2 + \tilde{\gamma}^T \Gamma^{-1}_\gamma \tilde{\gamma} + \tilde{\phi}^T \Gamma^{-1}_\phi \tilde{\phi} \right] \]
(2.70)

where \( \Gamma^{-1}_\gamma \) and \( \Gamma^{-1}_\phi \) are positive definite diagonal matrices representing learning parameters, and the tilde denotes the error between the estimated and real values (\( \tilde{\gamma} = \hat{\gamma} - \gamma; \tilde{\phi} = \hat{\phi} - \phi \)). It follows that (2.70) is positive definite and contains all time varying parameters. Neglecting the higher order term and specializing for the case where \( s > \Phi \), the time derivative of \( V \) is:
\[ \dot{V} = sP A e + sP B (\hat{\gamma}^T \hat{\phi} + \hat{\phi}^T \hat{\gamma} - m_c \hat{\gamma}^T \hat{\phi}) + \hat{\gamma}^T \Gamma^{-1}_\gamma \hat{\gamma} + \hat{\phi}^T \Gamma^{-1}_\phi \hat{\phi} \]
\[ + \tilde{\gamma}^T \Gamma^{-1}_\gamma \tilde{\gamma} + \tilde{\phi}^T \Gamma^{-1}_\phi \tilde{\phi} + sP B \epsilon - sP B \bar{u} - (1 - m_c) s |P B \bar{k} \]
\[ - sP B m_c u_{\text{max}} \text{sat} \left( \frac{s}{\Phi} \right) \]
\[ = e^T P^T P A e + \hat{\phi}^T \left( (1 - m_c) \hat{\gamma}^T B^T P^T s + \Gamma^{-1}_\phi \hat{\phi} \right) \]
\[ + \tilde{\gamma}^T \left( (1 - m_c) \hat{\phi}^T B^T P^T s + \Gamma^{-1}_\gamma \hat{\gamma} \right) - sP B (\bar{u} - \epsilon) - (1 - m_c) s |P B \bar{k} \]
\[ + \tilde{\xi}^T \Gamma^{-1}_\xi \tilde{\xi} - \phi^T \Gamma^{-1}_\phi \phi - sP B m_c u_{\text{max}} \text{sat} \left( \frac{s}{\Phi} \right) \]
(2.71)

with:
\[ \tilde{\xi} = \begin{bmatrix} \tilde{\gamma} \\ \tilde{\phi} \end{bmatrix}, \Gamma = \begin{bmatrix} \Gamma_\gamma & 0 \\ 0 & \Gamma_\phi \end{bmatrix} \]
2.4. WNN FOR SEMI-ACTIVE CONTROL

The tilde denotes the error between the optimal and current parameters, and $\xi$ represents aggregation of parameters $\gamma$ and $\phi$. By choosing the following adaptation laws:

$$
\dot{\gamma} = -(1 - m_c) (\Gamma_\gamma \hat{\phi}) B^T P^T s
$$
$$
\dot{\phi} = -(1 - m_c) (\Gamma_\phi \hat{\gamma}) B^T P^T s
$$
$$
\dot{\Gamma}^{-1} = -s^2 I
$$

where $I$ is an identity matrix to populate $\dot{\Gamma}^{-1}$, equation (2.71) becomes:

$$
\dot{V} = e^T P^T P A e - s P B (\bar{u} - \epsilon) - (1 - m_c) |s| P B k - \xi^T (s^2 I) \xi - \phi^T \Gamma_\phi^{-1} \phi - s P B m_c u_{sl}
$$

Choosing $k = u_b$, where $u_b$ is a known bound (also positive) on $\bar{u}$, (2.73) can be rewritten as:

$$
\dot{V} = e^T P^T P A e - s P B (\bar{u} - \epsilon) - (1 - m_c) |s| P B k - \xi^T (s^2 I) \xi - \phi^T \Gamma_\phi^{-1} \phi - s P B m_c u_{sl}
$$

Defining mathematically the subspaces illustrated in Fig. 2.13:

$$
C_d = \{ u_b \geq |\bar{u}| \mid u_b, \bar{u} \in \mathbb{R} \}
$$
$$
C_t = \{ u_b \geq \tau |\bar{u}| \mid \tau \in [0, 1], u_b, \bar{u} \in \mathbb{R} \}
$$
$$
C = \{ \bar{u} \mid \bar{u} \in \mathbb{R} \}
$$

$m_c$ is selected to make (2.74) as negative definite as possible:

$$
m_c = 0 \quad \text{if } \bar{u} \in C_d
$$
$$
0 < m_c < 1 \quad \text{if } \bar{u} \in C_t - C_d
$$
$$
m_c = 1 \quad \text{if } \bar{u} \in C - C_t
$$

Using (2.75), (2.74) can be rewritten:
\[
\dot{V} = e^T P^T P A e - s P B (\tilde{u} - \epsilon) - |s| P B u_b \\
- \tilde{\xi}^T (s^2 I) \tilde{\xi} - \tilde{\phi}^T \Gamma^{-1} \phi \\
\dot{V} = e^T P^T P A e - s P B (\tilde{u} - \epsilon) - |s| P B u_{\max} \\
- \tilde{\xi}^T (s^2 I) \tilde{\xi} - \tilde{\phi}^T \Gamma^{-1} \phi \\ 
\text{if } \tilde{u} \in C_d \\
\text{if } \tilde{u} \in C - C_t 
\]

The first term in (2.76) is negative semi-definite as the state-space matrix \( A \) is inherently stable for civil structures. The third term is bigger than the second term for \( \tilde{u} \in C_d \) and is as negative as possible for \( \tilde{u} \in C - C_t \), and the fourth term is negative definite. The last term in (2.76) arises from the use of a sequential adaptive scheme, whereas the radial wavelet functions evolve with time. This term represents the trade-off in designing an adaptive neurocontroller for a system assumed to be fully uncertain. Using Barbalat’s lemma and assuming that the first four terms are greater (in absolute value) than the last term, the error will converge to zero [171].

Noting that \( P^T P \) is always semi-positive definite, the condition on the sliding surface coefficients \( P \) to ensure stability is that the dynamics of the sliding surface itself be stable. This is achieved for \( P \) being a Hurwitz polynomial, which is the condition on the sliding surface for civil structures. Thus, coefficients of \( P \) can conveniently be taken as all non-negative, with their values representing control weights analogous to the matrix \( Q \) in LQR control. Unavailable states can be represented by zero coefficients.

It can be noted that the switching law in (2.66), represented by the term \( k \), can be used to control for system uncertainties. This is achieved by incorporating the error bound in \( k \), thus augmenting the control weight of the error metric \( s \), as shown in [171]. However, selecting \( k \) requires the knowledge of the error bound. The largest uncertainty in (2.66) is the uncertainty of the error on the applied force \( u_b \). This error can be quite large, and increasing its value too much would lead to a controller based almost exclusively on the sign of the sliding surface. Instead, a bound \( u_b \) is assumed, and adaptation on the network slowed or stopped when \( |\tilde{u}| > u_b \). Note that this adaptation rate is directly related to the sliding controller as \( k = u_b \). A sensitivity analysis of the controller with respect to \( u_b \) is included in the simulations.

The adaptation rules are in function of the matrix \( B \), assumed to be unknown. Since the magnitude of \( B \) can be easily evaluated and is of known sign, \( B^T P^T \) can be incorporated in the learning rate. It follows that the adaptation rules (2.72) are a version of the BP algorithm as they are written
2.4. WNN FOR SEMI-ACTIVE CONTROL

in the form \( \dot{\xi} = -\Gamma_\xi \delta(\gamma^T \phi)/\delta \xi \cdot s \). Therefore, without loss of generality, the adaptation rules can be written in discrete form:

\[
\begin{align*}
\hat{\gamma}_i(t + 1) &= \hat{\gamma}_i(t) - \Delta(1 - m_c)\Gamma_{\gamma_i} \hat{\phi}_i \text{sign}(B^T P^T) s \\
\hat{\mu}_{i,k}(t + 1) &= \hat{\mu}_{i,k}(t) - \Delta(1 - m_c)\Gamma_{\mu_i,k} \hat{\gamma}_i \\
&\quad \cdot \left( \frac{1}{\sigma_i} e^{-\frac{||\nu_k - \mu_i||^2}{\sigma_i^2}} \left( 4\sigma_i^2(\nu_k - \mu_i) - 2 ||\nu - \mu_i||^2(\nu_k - \mu_k) \right) \right) \\
\hat{\sigma}_i(t + 1) &= \hat{\sigma}_i(t) - \Delta(1 - m_c)\Gamma_{\sigma_i} \hat{\gamma}_i \\
&\quad \cdot \left( \frac{1}{\sigma_i} e^{-\frac{||\nu_k - \mu_i||^2}{\sigma_i^2}} \left( 4\sigma_i^2||\nu - \mu_i||^2 - 2 ||\nu - \mu_i||^4 \right) \right) \text{sign}(B^T P^T) s
\end{align*}
\]

(2.77)

where subscript \( k \) is the dimension of the neuron. Eq. (2.77) is the discrete adaptation law used for the simulations.

**Adaptive Learning Parameters**

Noting that \( \Gamma \Gamma^{-1} = I \), taking its time derivative results in:

\[
\dot{\Gamma} = \Gamma(s^2I)\Gamma
\]

(2.78)

It is clear from (2.72) and (2.78) that the adaptive learning rate can be any increasing function, because \( \dot{\Gamma}^{-1} \) has to be semi negative definite. Using the sliding surface error in the function is intuitive, as a greater error indicates that the system is further from its optimality, therefore increasing the step taken in the descent direction. The need for rapidly increasing steps is only making engineering sense in the cases when quick learning is prescribed, such as for earthquake loads. In the case of wind load, those rates could be stationary. In order to prevent the learning rate from augmenting too quickly, and thus initiating system instability, (2.78) is modified by dividing by the 2-norm of the learning rate. Therefore, noting that in the following equation \( \Gamma_\xi \) is the \( \xi \)th diagonal parameter of the matrix \( \Gamma \) and thus a scalar, the adaptation laws (2.72) for the \( \xi \)th network parameter can be rewritten as:
CHAPTER 2. CONTROL ALGORITHMS FOR LARGE PARAMETRIC UNCERTAINTIES

\[ \dot{\xi} = -\Gamma_{\xi}\left( \frac{\delta u}{\delta \xi} \right) \text{sign}(B^TP^T)s \]

\[ \dot{\Gamma}_{\xi} = s^2 \]

2.4.5 Discussion on Inputs, Time Delay, and Measurement Errors

The sliding surface necessitates the knowledge of all displacements and velocities, as well as for some of the input vector in (2.53). To obtain those states, it is generally better to have an estimator. In practice, as discussed in the previous chapter, only accelerations are measured because displacement and velocity measurements only provide relative quantities, are more expensive to measure than accelerations, and integration of acceleration can lead to significant errors [79]. However, it will be shown in the next chapter that the phase space of a time series can be reconstructed using the delayed measurements of a single observation from the force inputs and the state outputs [180, 85]. Thus, a vector of acceleration measurements can contain the essential dynamics of a system, provided that it is properly constructed. Thus, in the following chapter, we will show that the acceleration inputs could be used as neural inputs as they give enough information on the current state of the controlled system, provided that the input vector is adequately constructed, or that it is large enough to enclose all of the essential dynamics. In other words, the inputs for the iWNN controller will consist of local acceleration observations \( y \) and force inputs \( u_i \), delayed in time by a constant \( \tau \), and embedded in a dimension \( d \):

\[ \nu = [y_i(t), y_i(t - \tau), ..., y_i(t - (d - 1)\tau), u_i(t), u_i(t - \tau), ..., u_i(t - (d - 1)\tau)] \]

Therefore, each control device has a decentralized controller that relies on local measurements only. The sliding surface is constructed using local displacement and velocity measurements. Hence, the vector \( P \) will contain null entries where measurements are not available. In the simulations contained in Chapter 5, it is assumed that the control device displacements and velocities are measurable, which are related to inter-story states. Thus, \( P \) for a devices is constructed in the following form:
2.4. WNN FOR SEMI-ACTIVE CONTROL

\[
\begin{bmatrix}
p_{d1} & -p_{d1} & 0 & \cdots & 0 & 0 \\
p_{d2} & -p_{d2} & \cdots & 0 & 0 \\
& \ddots & \ddots & \ddots & \ddots & \ddots \\
0 & 0 & \cdots & p_{da} & -p_{da} \\
p_{v1} & -p_{v1} & 0 & \cdots & 0 & 0 \\
p_{v2} & -p_{v2} & \cdots & 0 & 0 \\
& \ddots & \ddots & \ddots & \ddots & \ddots \\
0 & 0 & \cdots & p_{va} & -p_{va} 
\end{bmatrix}
\]

where \(d\) and \(v\) denotes displacement and velocity degrees-of-freedom respectively.

Time delay can induce instability in a control system [40]. Even though the neurocontroller simulation time step remains under the sampling rate, the interaction sensor-controller-device will most likely induce a delay. If the delay is known, it can be implicitly fed in the neurocontroller by changing the lag time of each input. It can be also assumed that the neurocontroller will learn that the system has a delay, thus adapt. Measurement errors are also present in most controlled systems. An analysis of the controller performance with respect to time delay and measurement errors is included in the simulations (Chapter 5).

2.4.6 Discussion on the Control Objectives

It is important to understand the control objectives for civil structures in order to select appropriate network parameters. There exist two main regulatory control objectives: acceleration mitigation, and displacement mitigation. Acceleration mitigation is a serviceability criterion and is mostly applicable to moderate-to-high wind excitations. The evolution of the neurocontroller for acceleration mitigation can be achieved at a slow rate, as structural integrity is not of concern. This allows higher robustness for the algorithm. Adaptive learning rates are switched off for acceleration control.

Displacement mitigation is a concern during earthquake excitations, as structural integrity is at stake, and it is fundamental to minimize stresses and strains in structural members. The controller needs to optimally adjust rapidly. Impulse-like excitations quickly send the system in a new set of states away from the initial states. An aggressive learning strategy is recommended as a result of the neural network being in a control region whose control rules have yet to be constructed. To overcome the robustness issue arising from using high learning rates, the controller is built to \textit{forget} parts of the of the control rule that have been rapidly constructed [55]. The strategy is...
to identify nodes that have been created following an impulse loading. An impulse region is identified when the norm of the sliding surface error rate of change goes beyond a threshold. In the impulse excitation region, the target weight $\gamma_i$ is considerably increased based on the error norm, and incrementally forgotten in the following time steps. Adaptive learning rates are switched on for displacement control.

2.5 Conclusion

In this chapter, we have described various forms of controllers that can be used for robust control of uncertain systems. We have divided them into families of fixed and adaptive controllers. In our discussions, we have concluded that intelligent controllers, more precisely neurocontrollers, were more suited for controlling large-scale systems with large uncertainties. Consequently, we have presented an adaptive neurocontroller: the WNN, a single layer network of wavelet functions capable of self-organization and self-adaptation. Here, the innovation is the inclusion of a sliding controller, that allows the application of WNN for semi-actively controlled systems, or more generally to systems for which control devices have limited force reachability.

This chapter does not include simulations that demonstrate the performance of the WNN, as we have not yet presented in detail the input selection process. The performance of the WNN with pre-processed input selection has been discussed in [97], but we have recently argued that a pre-process input selection is quite difficult for uncertain dynamic systems. In the chapter that follows, we claim to have found a way to automate the input selection process, which will lead to a controller with limited state measurement. Such input selection scheme is far more realistic. The reader will appreciate much more the simulation results to come, once we will have explained the neural inputs for our WNN. Input selection is the central theme of the next chapter.
Organizing the Input Space
Chapter Notation

\( \alpha, \beta \) subset indices
\( \delta \) Euclidean distance
\( \Delta t \) time step
\( \gamma \) weight
\( \lambda \) Lyapunov exponent
\( \nu \) delay vectors
\( \phi \) wavelet function
\( \tilde{\phi} \) modal shape
\( \psi \) topological map
\( \sigma, \xi \) shift map
\( \tau \) time delay
\( \Lambda \) eigenvalue matrix
\( \Phi \) observation map
\( \Sigma, \Xi \) spaces
\( \mathcal{H}, \mathcal{M}, \mathcal{N}, \mathcal{O} \) spaces or sets
\( P, T, \tilde{T}, W \) spaces or sets
\( f, g, h \) maps
\( d \) dimension
\( f \) state function
\( g \) input function
\( h \) observation function
\( k \) discrete step
\( \tilde{f}, \tilde{f}', h \) maps
\( m, n \) numeric quantities
\( p \) probability
\( q \) local map
\( \tilde{q} \) modal coordinate
\( r \) distance
\( t \) time
\( u \) input or forcing
\( x \) state
\( y, \hat{y} \) observation
\( z \) spatial location

\( C \) correlation dimension
\( D \) Gram matrix
\( H \) Heaviside step function
\( H_{\text{MI}} \) entropy
\( I \) identity matrix
\( J \) Jacobian
\( \text{MI} \) mutual information
\( N \) quantity of \( n \)
\( Q \) quantity of \( q \)
\( R_{\text{A}} \) averaging function
\( R_{\text{A tol, tol}} \) tolerance thresholds
\( R_{d} \) neighbor distances
\( W \) weight matrix
\( \mathbb{R}, \hat{Y} \) set of observations
\( \emptyset \) empty set
3.1 Introduction

We have described in the Chapter 2 a controller developed for unknown systems equipped with semi-active devices. The controller is in essence a black-box model trained on a set of inputs-outputs. The control task can be generalized to a system identification problem, where we need to identify the control rule that should stabilize the system. We argue that, in the case of large-scale systems, the identification task needs to be achieved online and sequentially. One of the main challenges of online sequential identification is the input selection, as the time series is not typically known a priori. We make input selection the central theme of this chapter, as it directly impacts the number and location of sensors.

Before proceeding further, we shall describe some key concepts. Online is herein used to describe an identification process that is achieved in real-time, during an event, in opposition to offline, before or after the event as occurred. Sequential is used to define the identification algorithm as an adaptation process occurring at each time-step (whether it is online or offline), in opposition to batch training. The concept of online training is generally an obvious consequence of the sequential identification of a control rule. For instance, typical control mechanisms for large-scale structures are designed to ensure structural integrity. Thus, a controller is expected to always achieve a prescribed level of performance, where training shall be done immediately, online. If one would decide to generate data sets from laboratory experiments, large-scale systems can generally be only tested using small scale models due to technical and economical considerations, and those models are not necessarily close to reality because of the numerous assumptions required for constructing these models (the stiffness of the connections, for example).

The argument for sequential training arises from the nature of the excitations which typically originate from natural hazards. Despite that such excitations can be frequency-dominant, they are inherently highly stochastic. It results that batch training could misleadingly encompass different local dynamics in a training set, with the possibility of an inefficient and/or inaccurate adaptation. Sequential training, on the other hand, adjusts the controller directly based on the excitation as it evolves in time. Thus, adaptation is achieved locally, which allows the controller to adapt for local dynamics in the excitations, such as impulse loads arising from wind gusts or earthquakes.

Online sequential black-box adaptation needs to be computationally ef-
CHAPTER 3. ORGANIZING THE INPUT SPACE

Convergent. Convergence speed of these learning algorithms can be improved if the network size is minimal. Kohonen [91] proposed the self-organizing mapping (SOM) theory for neural networks, which organizes the hidden layer nodes so as to avoid unnecessary functions. It allows neural networks to be defined in a sub-region of the hyperspace where the system is evolving. Since the self-organizing theory was introduced, several adaptive topology schemes for neural nets have been proposed [107, 137, 95]. However, input representation, thus the selection of the hyperspace itself, has received little attention [22, 42]. The appropriate selection of the hyperspace has several advantages [228, 168, 22, 66, 96]:

- reduced computation due to a minimized representation of the hyperspace
- accelerated adaptation of the representation
- better understanding of the representation
- reduced effects of the curse of dimensionality
- reduced model complexity

Fig. 3.1 illustrates the concept via a trivial example. In Fig. 3.1a, a two-dimensional function \( f(x_1, x_2) \) is represented in a space \( \mathbb{R}^2 \) with a neural network (with fixed bandwidth and lattice for illustration purposes) covering the region with 9 nodes of 2-dimensional bandwidth. Fig. 3.1b is the same function in \( \mathbb{R}^3 \), where the neural network now needs 27 nodes of 3-dimensional bandwidth to cover the entire region. In contrast with the SOM theory which would allow localization of the nodes (from 27 or 9 nodes reduced to 4 nodes), a proper input selection would reduce the dimension of the nodes themselves from 3 to 2, enhancing computation speed.

Typically, the input space of a dynamic system can be selected a priori via time series analysis or heuristically. In the case of online sequential training, none of those general methods are available. This chapter introduces an algorithm, termed the Self-Organizing Inputs (SOI) algorithm, which is a strategy that allows selection and adaptation of the input space of a black-box model, online and sequentially. The proposed method is a general technique that could be applied to any black-box system identification or control scheme. Here, it will be applied in the context of our WNN. The reader
3.1. INTRODUCTION

will later appreciate that this dynamic organization of the input space has the tremendous advantage of using limited states for inputs, which converts to a limited need of sensors to control plants. In other words, the SOI algorithm allows control of systems with limited state measurements.

In this chapter, Section 3.2 provides theories from nonlinear time-series analysis that can be useful to the reader to grasp technical details used in the subsequent sections. Concepts of algebraic topology are reviewed, which are followed by some methods used to describe complexity of nonlinear time series: Lyapunov exponents, recurrence quantification analysis, and a homemade stationarity index. Section 3.3 reviews the problem of input selection for black-box modeling, and discusses techniques to reduce the dimensionality of dynamic systems. It also discusses the embedding theorem, which is the central dimensionality reduction technique of our SOI algorithm. Section 3.4 describes the SOI algorithm and discusses its extension to the class of nonstationary MDOF systems, as well as its sequential implementation. Section 3.5 lists the algorithm of the proposed WNN controller equipped with the SOI algorithm. Section 3.6 simulates the algorithm to demonstrate its performance. Section 3.7 concludes the chapter.
CHAPTER 3. ORGANIZING THE INPUT SPACE

![Figure 3.2: Illustration of the concept of topology a) a torus is not equivalent to a sphere; and b) a coffee mug is equivalent to a donut [2].](image)

3.2 Nonlinear Time Series Analysis

3.2.1 Algebraic Topology

Topology is the study of shapes and locations. In the theory of topology, shapes are allowed to deform, bend, fold, stretch, twist, etc., just like if they were made of rubber, but they cannot be ripped apart or punctured. For instance, in topology, a torus is not equivalent to a sphere, but a coffee mug is equivalent to a donut [2], as illustrated in Fig. 3.2.

A topological space is the studied object, and it is formed by a collection of subsets termed open sets. A topological manifold is a topological space. An embedding is a function mapping a topological space into another topological space. The same concept applies to algebraic topology, where objects are replaced by functions.

Mathematically, let $\mathcal{M}$ be any set and $\mathcal{N} = \{\mathcal{M}_\alpha\}$ be a collection of subsets $\alpha$ of $\mathcal{M}$. It can be said that $\mathcal{N}$ gives a topology to the topological space $\mathcal{M}$ formed of open sets $\mathcal{M}_\alpha$ if the following conditions are satisfied [139]:

1. $\emptyset \in \mathcal{N}, \mathcal{M} \in \mathcal{N}$
2. All subcollection $\{\mathcal{P}_\alpha\}$ of $\mathcal{M}$ satisfy $\cup \mathcal{P}_\alpha \in \mathcal{N}$
3. Any finite subcollection $\{\mathcal{P}_{\alpha_1}, ..., \mathcal{P}_{\alpha_n}\}$ of $\mathcal{M}$ satisfy $\cap \mathcal{P}_{\alpha_i} \in \mathcal{N}$
3.2. NONLINEAR TIME SERIES ANALYSIS

where $\emptyset$ denotes the empty set. A set $M \in \mathbb{R}^d$ is said to be *compact* if it is closed and bounded, where $d$ is the set dimension. A map is said to be *homeomorphic* if its map is continuous and its inverse is also continuous. A smooth, differentiable, homeomorphic map is *diffeomorphic*. For instance, a square is homeomorphic, but not diffeomorphic. A manifold $M$ is differentiable if [139]:

1. $M$ is a topological space
2. $M$ has a family of pairs $\{(M_\alpha, \psi_\alpha)\}$
3. $M$ is covered by a family of open sets $M_\alpha$ ($\bigcup_\alpha M_\alpha = M$). $\psi_\alpha$ homeomorphically map $M_\alpha$ to open subsets $O_\alpha$ of $\mathbb{R}^d$, $\psi_\alpha : M_\alpha \rightarrow O_\alpha$
4. Taking two overlapping collections $M_\alpha, M_\beta$ such that $M_\alpha \cap M_\beta \neq \emptyset$, the map $\psi_\beta \circ \psi_\alpha^{-1}$ from the subset $\psi_\alpha(M_\alpha \cap M_\beta)$ of $\mathbb{R}^d$ is infinitely differentiable.

The three first conditions ensure that $M$ is locally equivalent to an Euclidean space, and the last condition ensures that overlapping patches of subsets are smooth.

A map $\psi$ is said to be *one-to-one* if distinct points on a manifold $M$ map to distinct points on $\psi(M)$. In other terms, the map does not collapse points. Because of the well-defined correspondence of the real trajectory to its image, one-to-one maps have a great predictive power [162]. Embedding maps do not collapse points nor tangent directions. While the definition of an embedding map is more restrictive than the one-to-one map, it means that the set $M$ needs a well-defined tangent space. A map is termed an *immersion* if the Jacobian of the map $\psi$, $J\psi(x)$, has full rank, thus if the tangent space is well-defined for all points $x$ on $M$. A smooth map is both a one-to-one and an immersion of $M$. For instance, an embedding map is a smooth map. Those concepts are illustrated in Fig. 3.3.

The algebraic topology definitions given in this section will be used to describe some key concepts, explained later in this chapter, that have direct implications with the SOI algorithm. Beforehand, we need to describe some useful nonlinear time series analysis tools to describe the complexity of the time series. The next subsection explains Lyapunov exponents, which is a dynamic invariant used to quantify the level of chaos in a dynamic systems. It is followed by recurrence quantification analysis (RQA), which is a powerful
3.2.2 Lyapunov Exponents

The predictive capability of a time series depends on its complexity and level of chaos. For some chaotic systems, the forecast error can increase dramatically after only a few time steps ahead. The Lyapunov exponent can be used as a measure of the strength of chaos, or implicitly how well predictions can be made of a system. It measures how fast trajectories diverge.
3.2. NONLINEAR TIME SERIES ANALYSIS

The largest Lyapunov exponent is termed the *maximal Lyapunov exponent* (MLE). The MLE is a measure of how fast two points $x_1$ and $x_2$ distance over time, as illustrated in Fig. 3.4. Let $\delta_0$ be the Euclidean distance $\delta_0 = \|x_1(t) - x_2(t)\| \ll 1$ and $\delta_\Delta t$ the new Euclidean distance after a time step $\Delta t$: $\delta_\Delta t = \|x_1(t + \Delta t) - x_2(t + \Delta t)\| \ll 1$. The MLE $\lambda$ is given by:

$$\delta_\Delta t = \delta_0 e^{\lambda \Delta t} \text{ for } \delta_\Delta t \ll 1, \Delta t \gg 1$$

A positive $\lambda$ denotes *chaos*. A negative $\lambda$ denotes a *stable* system approaching a fixed point, or a *dissipative* system, while $\lambda = 0$ denotes a stable limit cycle and the system is called *marginally stable*. Systems with $\lambda = \infty$ are characterized as noise.

Several algorithms have been developed over the years to find the MLE of a data set. Among these, the algorithm developed by Rosenstein [158] gained popularity because of its computational speed and good precision. It consists of constructing a delay vector, finding the nearest neighbors by constraining temporal separations, measuring the average separation of those neighbors, and fitting a line to the data generated using the least squares method. The concepts of delay vector and nearest neighbors will be clarified in Section 3.3.2.
CHAPTER 3. ORGANIZING THE INPUT SPACE

3.2.3 Recurrence Quantification Analysis

RQA is a time series quantification tool that has been developed as a quantitative method to analyze recurrence plots [201]. Recurrence plots have been introduced in 1987 by Eckmann et al. [47] as visual tools to analyze time series. They consist of plotting a matrix of a time series against itself and indicating with a black dot when a pattern is repeated. By construction, the matrix is symmetric. Fig. 3.5 shows the recurrence plot of a time series (for a Duffing system, which will be defined later in Equation (3.29)). Black dots indicate the recurrence of a vector formed of delayed measurements \( \mathbf{\nu}_i \), when the Euclidean distance between \( \mathbf{\nu}_i \) and another vector \( \mathbf{\nu}_j \) is below an arbitrary distance \( r \).

In Fig. 3.5, one can notice series of patterns that are parallel to the diagonal line. Those patterns indicate determinism as close points remain close. Sparsity of dots indicate noise or an insufficient embedding dimension of the delay vector \( \mathbf{\nu} \). Determinism is indicated by the number of diagonals among dots. Stationarity can be observed by the homogeneity of the distribution of dots. The recurrence map can also be represented in colors. The color maps resemble contour maps where the colors give indications on the recurrence and are, of course, visually pleasing. Fig. 3.6 shows the color version of Fig. 3.5b. Dark blue indicates dots within the first radius (dark dots in Fig. 3.5b), and dark red indicates dots in the last radius.

RQA has been introduced as a quantitative method to study the recurrent
3.2. NONLINEAR TIME SERIES ANALYSIS

Figure 3.6: Recurrence map from Fig. 3.5b in color.

plots. Among the RQA measures that exist, five particular ones are of interest [201]:

1. **Recurrence**: The percentage of dots that are recurrent over the matrix.

   \[
   \% \text{ recurrence} = \frac{\text{number of recurrent dots}}{\text{matrix size}}
   \]  \hspace{1cm} (3.2)

2. **Determinism**: The percentage of dots that are forming diagonals over the recurrent dots.

   \[
   \% \text{ determinism} = \frac{\text{dots forming diagonals}}{\text{recurrent dots}}
   \]  \hspace{1cm} (3.3)

3. **Level of chaos**: The length of the longest diagonal. It is inversely related to the largest Lyapunov exponent.

   \[
   \text{chaos} = \max \text{ number of dots forming a diagonal}
   \]  \hspace{1cm} (3.4)
CHAPTER 3. ORGANIZING THE INPUT SPACE

4. Stationarity: The homogeneity of the distribution of recurrent dots. This is mathematically defined as the slope of the least squares regression of the percentage of local recurrence as a function of the orthogonal displacement from the central diagonal.

5. Grassberger-Procaccia dimension (GDP): The number of independent variable participating in the system, or a measure of complexity. The GDP is related to the recurrence by the following relationship:

\[ \text{number of recurrence} = r^{GDP} \]

where \( r \) is the absolute radius of the hypersphere enclosing the nearest neighbors.

3.2.4 Stationarity Index

As it will be mentioned later in this chapter, a central assumption for the SOI algorithm is local quasi-stationarity of time series. There exists many methods that aim at determining stationarity, but in the case of a finite time series, most methods can be unclear and ambiguous [124]. When using adaptive representations for controllers, the objective is to find a representation \( \tilde{f} \) of the function \( f \):

\[ u(k + 1) = f(x(k), u(k), t) \]

where \( x \) is the state or observation (note that in this section, we arbitrarily a one-to-one relationship between the observations and the states \( y = x \) in order to stay consistent with the notation from the field), \( u \) is the input, \( k \) is a discrete time step, and \( t \) is time. If one can show that, within a map \( q \) comprising \( n \) observations, the adaptive representation has not significantly changed such that \( \tilde{f}_{t=0} \approx \tilde{f}_{t=n} \), then (3.6) can be rewritten:

\[ u(k + 1) \approx \tilde{f}(x(k), u(k)) \]

within that map. Thus, the control force can be assumed to be stationary provided that the external excitations are also stationary. In the case of civil structures, moderate-to-high winds and earthquakes are the main types of excitations one would want to mitigate. Conveniently, the responses of an MDOF system subjected to a wind excitation can be assumed to be mutually independent Gaussian stationary processes [33]. Regarding earthquake, the
controller is designed for a quick adaptation and to forget the representation. Thus, convergence of the controller is not a concern. To determine the level of stationarity of local maps \( q \), a map will be declared stationary if the variation of the representation \( \tilde{f} \) within a map \( q \) is below a certain threshold. The percentage of stationary maps in function of the threshold will be the termed the *stationarity index*.

### 3.3 Input Selection

A large-scale system is inherently a multi-dimensional system. Take a 40-story civil structure for instance, and model it as a discrete shear beam. There are 40 nodes moving in one direction, and states include displacement, velocity and acceleration, for a total of 120 measurable states. Now, expand the model in 3 dimensions. A displacement in the perpendicular axis is added, as well as a rotation, for a total of 360 measurable states. Those states exclude bending of the structure, and assumes that inter-story displacements are constant across a floor, which is not the case for a geometrically large system. Thus, civil structure have thousands of measurable states, resulting in a necessity to identify a system in an hyperspace of very high dimension, which might lead to large computational difficulties.

Difficulties associated with working with a large dimensionality refer to the *curse of dimensionality* [101]. For instance, larger is the function hyperspace, larger the number of data sets are needed to fill the hyperspace in order to avoid empty spaces caused by sparsity of data. That number of data actually grows exponentially with the size of the space. A more compact representation is consequently more appealing. Practically, a compact representation means that less sensors are needed to measure and describe a dynamic system. Consequently, the possibilities of controlling based on limited measurements, or decentralized control. With the SOI algorithm, we aim at finding such compact representation, and we use it as direct inputs into the black-box representation. Therefore, the problem is to select the appropriate inputs, or the right sub-hyperspace, which will achieve the compact representation. In order words, we try to reduce the system’s dimension using appropriate variable selection. We consider in this thesis both terms *variable selection* and *dimensionality reduction* to be equivalent.

Variable selection, or input selection, is a topic that gained popularity in the past decade with the increase of model sizes and complexities. This
popularity, specific to the field of machine learning, has received little attention in identification of dynamic systems. There are several advantages of an optimal input selection, as enumerated in Section 3.1. Some techniques have been developed in order to find optimal inputs, but this optimality is often intractable due to the nonlinear relationship between the inputs and the outputs [66]. In 1997, several papers have discussed input selection [20, 90], but few domains had more than 40 variables [58]. Nowadays, it is not rare to have model representations evolving in hyperspaces with hundreds and thousands of dimensions.

The exists three main methods for input selection. First, there is the filter approaches, where the input selection is independent of the black-box model [20]. Second, the wrapper approaches, where the results from the black-box model are used to rank and select the inputs [90]. This method is obviously more computationally demanding. Third, the embedding methods, where selected inputs are used for adapting the black-box model [58]. Here, we are mainly interested by the embedding method, as it is the only feasible approach in the context of a sequential adaptation scheme. Typically, to verify the impact of the addition or suppression of an input, one would use model selection performance criteria such as Mallows’ $C_p$, [123], final prediction error [9], Akaike’s information criteria (AIC) [9], and the predicted residual error sum of squares statistic [15].

Among techniques utilized in the context of neural networks, Bonnlander and Weigend [21] and Battiti [17] discussed input selection using mutual information. Mao and Billings [125] and Yu [220] proposed variable selection based on a set of linearized models. Recently, Li and Peng [106] proposed a fast model to identify significant nonlinear terms in a function, which are used as neural inputs. Tikka [190] proposed a selection of radial basis function (RBF) network inputs by minimizing a constrained optimization problem.

The next subsection describes some key methods of dimensionality reduction for selecting an appropriate input space. It will justify the use of the embedding theorem for the SOI algorithm. The embedding theorem is discussed in the subsequent subsection.

3.3.1 Dimensionality Reduction Techniques

The previous section described some concepts about topology. The reader will see that these concepts are often used in the context of dimensionality reduction, which objective is to represent a system with as few inputs as
possible. Two benchmark problems are often used to assess the performance of dimensionality reduction techniques. They consist of the Swiss roll and the open box, shown in Fig. 3.7. The challenge is to use dimensionality reduction methods to represent those three-dimensional representation in only two dimensions. Visually, this is done by unrolling the Swiss roll and unfolding the open box. However, mathematically, those problems are not conveniently tractable.

The problems of the Swiss roll and the open-box can be extended to large-scale dynamic systems. They can be seen as numerous degree-of-freedoms represented in a very large hyperspace, and one needs to find a minimal representation to escape from the curse of dimensionality. Several techniques are available to analyze data sets and to find minimal representations. Among those are the principal component analysis (PCA), multidimensional scaling (MDS), and isomaps. This subsection will present those key dimensionality reduction techniques in order to justify the embedding theorem as the input selection strategy for the SOI algorithm. The reader is referred to [101] for a more complete discussion on nonlinear dimensionality reduction techniques.

PCA is an old dimensionality reduction method and counts several variations. Originally for linear representations, it has been extended to nonlinear representations and to online applications. The key concept of the PCA method is to represent the observations $y$ using an orthogonal matrix $W$.

Figure 3.7: The Swiss roll and the open box [101].
weighting latent variables $x$:

$$ y = Wx \tag{3.8} $$

where latent variables are defined as variables describing the dynamics of the observed data. By using the orthogonal matrix $W$ along with the minimization of an expected error, the PCA will return a minimal representation for the system. MDS resembles the PCA method, but uses the eigenvalue decomposition of distances between observations. Consider the Gram matrix $D$:

$$ D = y^T y = (Wx)^T (Wx) = x^T x \tag{3.9} $$

and take the eigenvalue decomposition of $D$:

$$ D = U \Lambda U^T = (U \Lambda^{1/2})(\Lambda^{1/2}U^T) \tag{3.10} $$

$$ = (\Lambda^{1/2}U^T)(\Lambda^{1/2}U^T) $$

it results that the latent variables can be written:

$$ x = I \Lambda^{1/2}U^{1/2} \tag{3.11} $$

as $W^T W = I$. The Gram matrix (3.9) represents an Euclidean distance measure. The problem with using the Euclidean distance is that it may lead to losses of information about the system. Take the Swiss roll for instance. Two points can be very close considering the Euclidean distance, but they are actually quite far in reality if the shape is unrolled, as shown in Fig. 3.8.

Tenenbaum et al. [187] discussed that specific issue with nonlinear dimensionality reduction, and proposed the isomap method. With this method, a graph is constructed by connecting all points that are neighbors using their Euclidean distances. Thereafter, the lengths of the paths between points within the graph are computed using the geodesic distance to create the distance matrix $D$. Consequently, a path needs to pass via the lines connecting dots. The embedding is constructed using the eigenvalue decomposition of $D$. Fig. 3.9 shows the 2-dimensional space constructed from the Swiss roll.
3.3. INPUT SELECTION

Figure 3.8: Two points on the Swiss roll. The Euclidean distance (dotted line) versus the geodesic distance (full line) [187].

Figure 3.9: Embedding the Swiss roll in 2 dimensions. The red line corresponds to the geodesic distance. It is shown in the reconstructed space (right) that the shortest distance between points is preserved (straight blue line) [187].

In essence, those methods take the observations, and attempt to construct a topological space of minimal dimension. The three techniques presented in this section have been presented as an evolution, where the MDS was a modified version of the PCA using the Euclidean distance metric to construct the topological space, and the isomap was an evolution of the MDS, where the geodesic distance is used in lieu of the Euclidean distance. Of course, the methods are much more sophisticated than presented, and their differences are not as straightforward.

The technique used here for dimensionality reduction, or control with
limited measurements, is the embedding theorem and is described in the next section. In short, the embedding theorem takes only a few observations, and tries to reconstruct a phase-space that represents the dynamics of the modeled system. It is different than the previous techniques in the sense that the latent variables $x$ are assumed, but similar to the isomap where the geodesic distances will be required, because the shape of the phase-space will have a one-to-one relationship with the unknown phase-space of the system.

### 3.3.2 Embedding Theorem

The field of nonlinear dynamics and chaos modeling studied the effect of dimensionality selection [7], where numerous theories have emerged from the celebrated Takens embedding theorem [185] that have been applied for analysis and identification of time series [200, 29, 65, 140, 132]. Takens showed in 1980 that the phase-space of an autonomous dynamic system:

$$x(k+1) = f(x(k)) \tag{3.12}$$

in a manifold $\mathcal{M}$ can be diffeomorphically mapped to another phase-space constructed from a single measurement, where $x$ is the state and $k$ is a discrete step. In other terms, a one-to-one map exists between both phase-spaces, and all of the coordinate-independent properties are preserved. Fig. 3.10 illustrates the concept. In the figure, the phase-space reconstructed from the measurements of the unknown system is geometrically equivalent to the phase-space of the unknown system.

The reconstructed phase-space is created using a vector $\nu$, termed the *delay vector*, which in turn is built using a time delay $\tau$ and embedding
3.3. INPUT SELECTION

dimension \(d\) of a single measurement \(y\):

\[
\mathbf{\nu}(k) = \begin{bmatrix} y(k) & y(k - \tau) & y(k - 2\tau) & \ldots & y(k - (d - 1)\tau) \end{bmatrix} = \Phi(x(k))
\]

(3.13)

where \(\Phi : \mathcal{M} \rightarrow \mathbb{R}^d\), and \(\tau = a\Delta t\), with \(\Delta t\) being the sampling rate and \(a\) is a positive integer. Not any value of \(\tau\) and \(d\) would lead to a geometrically equivalent phase-space. Therefore, the challenge is to find the values of \(\tau\) and \(d\) that will lead to the reconstructed phase-space from which a one-to-one map exists with the phase-space of the unknown system.

Several techniques exist to select an appropriate time delay \(\tau\) and embedding dimension \(d\). Intuitively, \(\tau\) has to be large enough such that \(y(k - \tau)\) gives additional information on the dynamics. For instant, if \(\tau = 1\), the phase-space is collapsed on a 45° line, and \(y(k) \approx y(k - 1)\). Thus, \(\tau\) has to be large enough to unfold the phase-space, but not too large as the phase-space will fold back. The embedding \(d\) has to encompass all of the essential dynamics. However, a large \(d\) may contain too much redundant information, and might result in a degradation of precision. Techniques for selecting \(\tau\) and \(d\) will be discussed later in this section.

Using (3.13), the function \(f\) can be written:

\[
\tilde{f} = \Phi \circ f \circ \Phi^{-1}
\]

(3.14)

where \(\circ\) denotes function composition, and tilde denotes a function representation. Applying (3.13) to (3.14):

\[
\tilde{f}(\mathbf{\nu}(k)) = \Phi \circ f \circ \Phi^{-1}(\mathbf{\nu}(k)) \\
= \Phi \circ f \circ \Phi^{-1}(\Phi(x(k))) \\
= \Phi \circ f(x(k)) \\
= \Phi(x(k + 1)) \\
= \mathbf{\nu}(k + 1)
\]

(3.15)

shows the equivalence between \(f\) and \(\tilde{f}\), and that the coordinate-independent properties are preserved. In essence, the theorem states that, given the observation \(y(k)\), it is possible to predict future observations using a map constructed from \(\mathbf{\nu}(k)\).
CHAPTER 3. ORGANIZING THE INPUT SPACE

Takens theorem has been extended to a general class of nonautonomous systems with deterministic forcing [179], state-dependant forcing [24], and stochastic forcing [180]. The authors proved that such systems can be diffeomorphically mapped using a delayed vector constructed with delayed inputs and observations. To understand the theorem, it is useful to think of the state-space of the nonautonomous system being expended sufficiently to make the system autonomous. For instance, taking a general dynamic system of the form:

\begin{align}
  x(k+1) &= f(x(k), u(k)) \\
  u(k+1) &= g(y(k), u(k)) \\
  y(k) &= h(x(k), u(k))
\end{align} \tag{3.16}

with \( x \in \mathcal{M} \), where \( \mathcal{M} \) is a smooth compact manifold, the forcing \( u \) can be taken in its own space \( u \in \Sigma \), where \( \Sigma \) is a shift space with its associated shift map \( \sigma : \Sigma \to \Sigma \) such that:

\[ \sigma(u(k)) = u(k+1) \tag{3.17} \]

The state of the nonautonomous system (3.16) evolves in the skew product \( T : \mathcal{M} \times \Sigma \to \mathcal{M} \times \Sigma \), where the skew product is defined as [180]:

\[ T(x, u) = (f(x, u_0), \sigma(u)) \tag{3.18} \]

Fig. 3.11 is a graphical representation of the phase shift concept.

The question is whether two different dynamic systems \( T \) and \( \tilde{T} \) can be equivalent such that \( \tilde{T} = H \circ T \circ H^{-1} \) for some invertible coordinate change \( H : \mathcal{M} \times \Sigma \to \mathcal{M} \times \Sigma \). One can observe that the space \( \mathcal{M} \times \Sigma \) can be infinite dimensional, and that the observations \( \nu \) depend solely on \( \mathcal{M} \). Hence, it is not possible to reconstruct the space \( \Sigma \) using only \( \nu \). Some restriction on \( H \) have to be imposed. A strategy is to let the space \( \Sigma \) untouched by only considering sets of the form \( H = (h, I) \) for some map \( h : \mathcal{M} \times \Sigma \to \mathcal{M} \), where \( I \) is the identity matrix and is associated with the components of \( \Sigma \). Thus, the map \( h \) can be written \( h_u = h(\bullet, u) : \mathcal{M} \to \mathcal{M} \), where \( \bullet \) denotes components associated with \( \mathcal{M} \).

Defining the skew product \( \tilde{f} : \mathcal{M} \times \Sigma \to \mathcal{M} \) by \( f'(x, u) = f(x, u_0) \), \( \tilde{T} \) can be written:
3.3. INPUT SELECTION

Figure 3.11: Illustration of the phase shift (adapted from [180]).

\[ \tilde{T} = (\tilde{f}', \sigma) = \mathcal{H} \circ \mathcal{I} \circ \mathcal{H}^{-1} \]
\[ = \mathcal{H} \circ (f', \sigma) \circ \mathcal{H}^{-1} \]
\[ = (h, I) \circ (f', \sigma) \circ (h, I)^{-1} \]  
\[
(3.19)
\]

Similarly to (3.15), using a new delay vector \( \nu = (\bullet, u) \) where \( h_u = h(\nu) \), (3.19) can be written:

\[
\tilde{T}(\nu_t) = (h, I) \circ (f', \sigma) \circ (h, I)^{-1}(\nu_t)
\]
\[
\tilde{T}(\bullet, u) = (h, I) \circ (f', \sigma) \circ (h, I)^{-1}(\bullet, u)
\]
\[
(\tilde{f}', \sigma')(\bullet, u) = (h, I) \circ (f', \sigma) \circ (h_u^{-1})
\]
\[
(\tilde{f}', \sigma(u)) = (h, I) \circ (f'_u \circ h_u^{-1}, \sigma(u))
\]
\[
(3.20)
\]

We note by inspection that (3.20) is similar to (3.15). Consequently, the observation vector \( \nu \) becomes:

\[
\tilde{f}'_u = h(\nu) \circ f'_u \circ h_u^{-1}
\]
\[ \nu = \begin{bmatrix} y_t & y_{t-\tau} & y_{t-2\tau} & \cdots & y_{t-(d-1)\tau} & u_t & u_{t-\tau} & u_{t-2\tau} & \cdots & u_{t-(d-1)\tau} \end{bmatrix} \]

\[ = \Phi(x, u) \]

\[ = \Phi_u(x) \]

\[ = \Phi_u(x(t)) \]

where \( \Phi \) is now a map \( \Phi_u : \mathcal{M} \times \Sigma \rightarrow \mathbb{R}^{2d} \).

Recent research has extended the delay embedding theorem to forced systems and to more restrictive classes. For instance, Széliga et al. [184] used a neural network to model a slowly varying nonstationary system. Nonstationarity has also been addressed by Hegger et al. [63] and Verdes et al. [194]. The authors proposed to cope with nonstationarity by overembedding the delay vector. Hirata et al. [65] studied embedding strategies for multivariate time series via nonuniform embedding. Meng & Peng [128] developed an embedding strategy for locally varying dynamics. The authors used information on local dynamics to construct an embedding map. Monroig et al. [132] extended the embedding theorem to the case of forced systems with multivariate observations where inputs are unknown. The authors showed that such system can be embedded using the delayed measurements of two distinct observations. Let the manifold \( \mathcal{M} \) be defined as the skew product of two compact manifolds \( \mathcal{M} : \mathcal{M}_\alpha \times \mathcal{M}_\beta \), where the state \( x \) lies in \( \mathcal{M} \) and can be decomposed as \( x = \{ x_\alpha, x_\beta \} \). Assuming a map \( f' : \mathcal{M} \times \Sigma \rightarrow \mathcal{M} \) exists, then there is a unique determination of the input \( u \) from the state \( x \):

\[ x_\alpha(k + 1) = f_\alpha(x(k), u(k)) \]
\[ x_\beta(k + 1) = f_\beta(x(k), u(k)) \]  

(3.22)

Consider that the input is unknown. Taking the map \( f_{\beta,x} = f_\beta(x, \bullet) \) as embedding for each \( x \in \mathcal{M} \), using (3.22) the input can be reconstructed:

\[ u(k) = f^{-1}_{\beta,x}(x_\beta(k + 1)) \]  

(3.23)

so that:

\[ x_\alpha(k + 1) = f_\alpha(x(k), f^{-1}_{\beta,x}(x_\beta(k + 1))) \]
\[ x_\alpha(k + 1) = g(x_\alpha(k), x_\beta(k), x_\beta(k + 1)) \]  

(3.24)

112
Thus, the delay vector (3.21) can be written:

\[
\nu(k) = \Phi(x(k), u(k)) = \Phi(x_a(k), x_\beta(k), x_\beta(k + 1))
\]  

(3.25)

with \( \Phi : \mathcal{M} \times \Sigma \to \mathbb{R}^d \). The direct application for us is that the embedding theorem can still be applied to systems with unknown forcings, which is the case for structures subjected to wind excitations.

The delay embedding theorem has been applied in many fields for model prediction, system identification, and control. More specifically, in the work done with neural networks, Stark et al. [178] used radial basis functions with a sequential recursive least square algorithm for short term prediction of chaotic time series. Cao et al. [29] introduced wavelet neural networks (WNN) for chaotic time series prediction. Principe et al. [154] used local nonlinear embedding maps with a self-organizing mapping neural network, and applied it to system identification and control. Plagianakos & Tzanaki [152] used a neural network to predict an earthquake excitation selecting inputs based on the embedding theorem. Walker et al. [196] utilized the same strategy to design a radial-basis model for modeling of an electronic circuit with dynamic effect. Leung et al. [102] used a radial basis function network which topology was optimized using the cross-validated subspace method. Shen et al. [164] proposed a predictive control scheme for chaotic systems using a neural network to make predictions. daSilva et al. [42] forecasted short term electricity loads, and noted the paramount importance of a proper input selection for short term prediction. Zolock & Greif [230] used a neural network to predict wheel/rail responses of rail vehicles.

Applications to the field of civil engineering are limited. The embedding theorem has been successfully applied to structural health monitoring. Moniz et al. [130] used chaotic excitations to reconstruct the phase-space of a system and detect the presence and magnitude of damage. Overbey et al. [150] studied the effectiveness of band-limited, stochastically generated noise, such as ambient vibrations, to detect changes in the vibration signature. Monroig [131] used the embedding theorem to detect changes in large nonlinear systems.

Based on the review of the literature, the embedding theorem has never been applied online. Such application would be beneficial for adaptive neural networks. A large class of neurocontrollers are of the form (3.16) where the
CHAPTER 3. ORGANIZING THE INPUT SPACE

force output depends on the state input. However, adaptive black-boxes, herein described as online mechanisms, fall into a class of nonstationary systems, because the control feedback $g$ is allowed to evolve with time:

$$
x(k + 1) = f(x(k), u(k, t))
$$
$$
u(k + 1) = g(y(k), u(k, t))
$$
$$
y(k) = h(x(k), u(k, t))
$$

We have developed the SOI algorithm in search of a strategy to apply the embedding theorem to nonstationary systems in real-time. At this point, the reader might be eager to know how $\tau$ and $d$ are selected for the construction of $\nu$. Thus, before proceeding to the algorithm itself, the next subsections review the existing theory for the design of the delay vector.

Time Delay

The choice of an appropriate time delay $\tau$ is fundamental for topologically representing the dynamics of a system. If $\tau \to 0$, the phase space will collapse on the 45° line. Visually, we need to increase $\tau$ until the phase space unfolds up to the point when it begins to fold back on itself, or when the coordinates become unrelated, but overparametrization of time delay can have disastrous consequences on the performance of the representation [228]. Among traditional techniques for selecting time delay, taking the value when the autocorrelation of the time series first crosses zero has often been used. Some authors chose a similar approach, but for values close to zero or at mid point [141]. However, the autocorrelation function is a linear relationship between data, and it can be misleading when used for nonlinear systems. Measuring the general dependence between two variables, termed the mutual dependence, is more suited for nonlinear systems [50]. This technique measures the average information gained from a new measurement, or how well can the outputs $\hat{Y}$ be measured given the measurements $Y$. Fraser and Swinney [50] presented the theory for mutual information based on Shannon’s information theory:

$$
\text{MI}(\hat{Y}, Y) = H_{\text{MI}}(\hat{Y}) - H_{\text{MI}}(\hat{Y} | Y)
$$
$$
= H_{\text{MI}}(\hat{Y}) + H_{\text{MI}}(Y) - H_{\text{MI}}(Y, \hat{Y})
$$

114
where $H_{MI}$ is the entropy, representing the average information gained from a measurement $\hat{y}$ or $y$, or the average uncertainty of an output $\hat{y}$ given the measurement $y$. In term of probabilities, (3.27) has the form:

$$MI(\hat{Y}, Y) = -\sum_{i} p_{\hat{y}_i} \log_2 p_{\hat{y}_i} - \sum_{j} p_{y_j} \log_2 p_{y_j} + \sum_{i} \sum_{j} p_{\hat{y}_i y_j} \log_2 p_{\hat{y}_i y_j}$$  \[3.28\]

The first local minima of the MI test gives the optimal time delay, while subsequent minima correspond to a system that has exceedingly unfolded.

We take a Duffing system to illustrate the concept. The system dynamics is given by:

$$\dot{x}_1 = x_2$$
$$\dot{x}_2 = -0.1 x_2 + 0.5(x_1 - x_1^3) + 0.11 \sin x_3$$
$$\dot{x}_3 = 0.79$$  \[3.29\]

Its phase-space is plotted in Fig. 3.12a, and the results from the MI test shown in Fig. 3.12b. The phase-space of the delayed vector of dimension 2 is shown in Fig. 3.13 for different time delays. Fig. 3.12b shows that the mutual information test gives an optimal time delay $\tau$ of 22. Fig. 3.13 confirms that the phase-space of the delayed vector unfolds from $\tau = 1$ to $\tau = 22$, and then gradually folds back.

**Embedding Dimension**

The embedding dimension of the input vector can be seen as the dimension of the adaptive functions. Knowing the optimal value for $d$ results in an optimal computation time, because the system dynamics can be represented minimally. A value larger than the optimal $d$ would still lead to a consistent representation of the state-space, but there would be redundancy in data, which could result in a degradation of precision. In the context of a neural system, this means that knowing the optimal dimension $d$ would result in a minimal-size network on the input side [50].

It has been shown that a sufficient dimension is one that is larger than twice the fractal dimension, a measure of how completely a fractal appears to
Figure 3.12: a) The phase-space Duffing system in continuous form ($x_t$ versus $x_{t-1}$); b) the mutual information function with its minimum indicated by the dot.

Figure 3.13: Unfolding of the phase-space of the Duffing system ($x(t)$ versus $x(t - \tau)$).
3.3. INPUT SELECTION

fill a set. However, measuring the fractal dimension is difficult for dimensions higher than 2 [169]. There exists another measure for dynamic systems termed correlation dimension. The correlation dimension can be computed from a time series and is represented as the fraction of all possible pairs of points that are closer than a distance $r$:

$$C(r) = \lim_{N \to \infty} \frac{1}{N^2} \sum_{i,j=1}^{N} H(r - \|x_i - x_j\|)$$  \hspace{1cm} (3.30)

where $H$ is the Heaviside step function. The function described in (3.30) behaves as a power function and can be written as:

$$C(r) = r^m$$  \hspace{1cm} (3.31)

where $m$ is termed the correlation dimension and is closely related to the fractal dimension [169].

Other methods have also been suggested, such as the false nearest neighbors (FNN) method [86]. With this method, if a point is a nearest neighbor in the phase-space in Euclidean term, then this distance should not change by increasing the embedding dimension if those points are effectively nearest neighbors. In order words, the FNN method attempts at discovering a topological space where the geodesic ordering is preserve. Note that the neighbors in the phase-space can actually be distanced points in the time series. Fig. 3.14 shows the relationship between local neighbors in the phase space and the time domain.

Wayland et al. [200] used the FNN technique to develop a qualitative measure of determinism of time series. Kennel et al. [86] described an algorithm for determining the embedding dimension based on the FNN method. The technique consists of starting at $d = 1$, and computing the nearest neighbors $r$ from a point $y(n)$. Thereafter, the dimension is increased, and the distances $R_d(n,r)$ is computed. If the change is above a certain threshold $R_{tot}$, then a false neighbor is discovered. The dimension is increased until the percentage of false neighbors converges to zero. Mathematically, a false neighbor is discovered if:

$$\left| \frac{R^2_{d+1}(n,r)}{R^2_d(n,r)} - \frac{R^2_{d}(n,r)}{R^2_d(n,r)} \right| > R_{tot}$$  \hspace{1cm} (3.32)

The authors also added a second condition to ensure that nearest neighbors are also close to each other. This condition is written:
Figure 3.14: Time series and local neighbors (adapted from [154]).

\[
\frac{R_{d+1}(n)}{R_A} > R_{A,tol}
\]  \hfill (3.33)

with:

\[
R^2_A = \frac{1}{N} \sum_{n=1}^{N} (z(n) - \bar{z})^2
\]

where \( N \) is the number of points, \( z \) is the space location of the new point added with the new dimension, \( \bar{z} \) is the arithmetic average of \( z \), and \( R_{A,tol} \) is a threshold. The reader needs to be aware of the numerous crossings that appear in the phase-space for nonautonomous systems. It causes some
neighbors that are tested as false neighbors to actually be true neighbors where those crossings occur [150].

To illustrate the embedding dimension concept, the example of the Hénon map from Kennel et al. [86] is taken. This example has been taken because of its possibility to be visually represented in all dimensions. The dynamic system is given by:

\[
\begin{align*}
    x_1(k+1) &= 1 - 1.4x(k)^2 + x_2(k) \\
    x_2(k+1) &= 0.3x_1(k)
\end{align*}
\] (3.34)

The Hénon map is the autonomous system represented in Fig. 3.15a, along with the results from the FNN test in Fig. 3.15b. Fig. 3.15b suggests an embedding dimension \( d = 2 \).

Fig. 3.16a shows the delayed vector (constructed with \( \tau = 1 \)) embedded in one dimension. Three closest neighbors are marked on the graph. Note that because of the high density of points, the three dots overlap. Fig. 3.16b shows the delayed vector embedded in two dimensions. The same neighbors are dotted on the graph. It is clear that two of the closest neighbors were false neighbors. Fig. 3.16c shows the delayed vector embedded in three dimensions. All neighbors from Fig. 3.16b remain neighbors.

The RQA from section 3.2.3 can also be used to visually evaluate a proper embedding dimension. The objective is increase the embedding dimension until the sparsity of dots sufficiently decreases. Mathematically, one needs to increase the embedding dimension until the level of percentage of determinism
Figure 3.16: Delayed vector embedded in a) one dimension; b) two dimensions; c) three dimensions.

is above a threshold. Fig. 3.17 illustrates the recurrence plot of a section of the ElCentro 1940 North-South (NS) component time series. It can be observed that the embedding dimension $d = 4$ leads to significant noise, while $d = 6$ shows a well-behaved recurrence plot. The embedding vector $d = 8$ is over-embedding. Fig. 3.18 is a color map of the embedding $d = 6$. Note that in the case where the time series is not known apriori, the RQA method is certainly not suited for finding a value for the embedding dimension of the delay vector. Nevertheless, it is a good tool to visually represent the level of stationarity of time series, as aforementioned.
3.4 Self-Organizing Algorithm

In search of proper selection of inputs, we developed a strategy to build the delayed vector $\nu$ automatically. This strategy is the proposed SOI algorithm. The SOI algorithm is designed to investigate the phase-space of the controlled system, and select the dynamic inputs that would capture its essential dynamics. Those inputs can be directly used as black-box modeling inputs, because they give an accurate representation of the system to be modeled. It has the tremendous advantages to take the input selection out of the design process, and also accelerate training using a better representation.

Figure 3.17: Recurrence plot of a section of the ElCentro 1940 NS component time series with an embedding dimension of: a) $d = 4$; b) $d = 6$; and c) $d = 8$. 
of the system dynamics. The SOI algorithm is novel by its capability to sequentially organize, online, the input space of a neural network, analogous to the self-organizing maps developed by Kohonen [91] for the hidden layers. It sequentially computes an optimal time delay and embedding dimension for the input space using a moving window on the last $n$ observations. The moving window allows the computation time to remain smaller than the sampling rate, and lets the neural network adapt to local dynamics (or to the global dynamics of the last $n$ observations). The input space is adapted accordingly, sequentially and online, at each time step. Applying a sequential and online organization of the input space allows the neural network to adapt to local dynamics, which results in a more efficient and optimal input space. A direct consequence is an improved predictive and control capability. Fig. 3.19 schematically represents the SOI algorithm in the closed-loop system. A time window memory keeps track of the last $n$ observations, the SOI algorithm selects values for $\tau$ and $d$, the delay vector $\nu$ is constructed and used as inputs in the adaptive black-box model, which in turns outputs a required control force.

Figure 3.18: Color map of Fig. 3.17b.
3.4. SELF-ORGANIZING ALGORITHM

The next subsections discuss nonstationarity, explain the detailed sequential construction of the delayed vector, and show that the SOI algorithm can be applied to multiple input - multiple output (MIMO) systems.

3.4.1 Nonstationarity

The embedding theorem discussed in section 3.3.2 is applicable to stationary systems. Because online adaptive black-box models are by nature nonstationary, the question is whether or not the theorem still holds. The way the SOI algorithm cope with nonstationarity is by utilizing local dynamics. The embedding theorem presented previously assumes that a system is define by a single map \( f \), thus a map constructed from the entire, or global, dynamics. Another strategy is to write a function representation \( \tilde{f} \) in terms of several local maps \( \tilde{f}_q \) for \( q = 1, ..., Q \) [154]:

\[
\tilde{f} = \bigcup_{q=1, \ldots, Q} \tilde{f}_q
\]

Adaptive representations can be seen as nonlinear feedback loops where the feedback parameters are allowed to vary. For instance, taking a single-layer wavelet neural network and specializing for a single output:

![Schematic representation of the SOI algorithm.](image-url)
where $u$ is the output, $\gamma$ are weights, $\phi$ are wavelet functions, $\nu$ is the delayed vector used as input, and $n$ is the number of nodes, the output can be represented by a shift map $\xi$ modified from (3.17) where $\xi : \Sigma \times \Xi \to \Sigma \times \Xi$:

$$
\xi(u(k), t) = u(k + 1) \tag{3.37}
$$

Let the manifold $\mathcal{M}$ be discretized locally such that $\mathcal{M} = \bigcup_{q=1}^{Q} \mathcal{M}_q$, where the shift map $\xi$ is assumed to be stationary or quasi-stationary for each local map in $Q$. Note that $\xi$ is smooth and compact, because the evolution of the adaptive parameters in (3.36) are restricted to be smooth and compact to ensure stability of the neural net. The shift map can be written $\xi = \bigcup_{q=1}^{Q} \sigma_q$. Thus, similar to the idea that nonautonomous stationary systems can be made autonomous by sufficiently expending the phase space, the system is now allowed to evolve over the manifold $\mathcal{W}$ where $\mathcal{W}$ is globally defined as the skew product $\mathcal{W} : \mathcal{M} \times \Sigma \times \Xi \to \mathcal{M} \times \Sigma \times \Xi$, or locally defined as:

$$
\mathcal{W} : \bigcup_{q=1}^{Q} \{ \mathcal{M} \times \Sigma \}_q \tag{3.38}
$$

The smoothness of the shift map $\xi$ allows the system to be written in the form of (3.38). Essentially, the representation resembles (3.18), except that time is shifted along $\Sigma \times \Xi$ instead of $\Sigma$ alone. Fig. 3.20 illustrates the local representation. Note that as $Q \to \infty$, $\Sigma \times \Xi \to \Xi$. Hence, for a large number of local maps $Q$, the same delay vector as (3.21) can be used to embed $\mathcal{W}$.

To allow the SOI algorithm to use local representations, a sliding window is used over the last $n$ observations. At each time step, the time delay $\tau$ and embedding dimension $d$ are computed and the input space adapted accordingly. Not only the sliding window allows to cope with nonstationarity, but it is also accounting for local dynamics in the predicted or controlled system.
3.4.2 Sequential Construction of the Delayed Vector

For the sequential adaptation, it is assumed that:

- \((x(k), u(k)) \approx (x(k + 1), u(k + 1))\)
- the embedding dimension \(d\) is small
- the evolution of the representation for the addition and suppression of dimensions is smooth

These assumptions ensure that changing the time delay from one time step does not affect significantly the nature of the inputs, thus guaranteeing robustness of the adaptive representation. Using this assumption, a mutual information test \((9)\) is done on the range \([\tau(k) - 1, \tau(k) + 1]\), and \(\tau\) is chosen for which a local minima has been detected over the range, or \(\tau(k + 1)\) if no local minima has been detected.

From the discussion on the techniques available to compute the embedding dimension, it appears that the most suitable technique for adaptive representations is the FNN method due to its simplicity. To use the FNN method sequentially, the FNN test is also conducted in the search space \([d(k) - 1, d(k) + 1]\). The embedding dimension is only allowed to increase by one unit at each time step to maintain robustness. Moreover, to avoid unnecessary high variations in the input space, parameters are updated only
CHAPTER 3. ORGANIZING THE INPUT SPACE

if the update has been required for a certain number of steps, which improves the smoothness of the adaptation.

3.4.3 Extension to MIMO systems

MIMO systems inherently have several measurable nodes and states, and of different scales. For instance, accelerations in (g) and control forces in (N) can differ by a magnitude of $10^6$. Without appropriate scaling, the force input would have a significantly higher importance in the representation. It is necessary to scale multivariate observations to avoid such phenomena. Scaling of multivariate data can lead to numerically more stable representations with improved convergence [145]. Multiple states can also be included in the delay vector. This is simply achieved by incorporating the additional variables by utilizing the same values for the time delays and embedding dimensions. Nevertheless, implementing several output observations will result in a high dimensional space, and some black-box systems such as wavelet networks are not suited for such problems [19]. It is numerically preferable to use a single state observation along with the measured force inputs.

The question is which state measurement one should use if many measurements are available. Consider a system where the state being identified or controlled, here termed the objective state $x_k$, is different than the observed state $x_j$. The available measurements must be topologically equivalent to the objective state. Modal decomposition can be used to show that a map exits between two different degree-of-freedoms of a system, provided that they are not null point nodes. Null point nodes are herein defined as stationary (not to be confused with the concept of stationarity in time series) modal nodes. The response of a MIMO system can be decomposed into modes:

$$\dot{x} = \sum_{i=1}^{n} \dot{q}_i(t)\tilde{\phi}_i$$  \hspace{1cm} (3.39)

where $n$ is the number of degree-of-freedom, $\dot{q}$ is the modal coordinate, and $\tilde{\phi}_i$ is the $i^{th}$ modal shape vector. Thus, the response of a single observation can written:

$$\dot{x}_j = \sum_{i=1}^{n} \dot{q}_i(t)\tilde{\phi}_{j,i}$$  \hspace{1cm} (3.40)
where $\tilde{\phi}_{j,\bullet}$ is the vector of the $j^{th}$ components of the modal shape vector. Assuming that the degree-of-freedoms being mapped are not stationary nodes, a map $g$ exists such that $\tilde{\phi}_{k,\bullet} = g(\tilde{\phi}_{j,\bullet})$ where $k$ is another component of the modal shapes. The response of another state can be obtained using:

$$
\dot{x}_k = \sum_{i=1}^{n} \dot{q}_i(t) \tilde{\phi}_{k,i}
= \sum_{i=1}^{n} \dot{q}_i(t) g(\tilde{\phi}_{j,i})
= \sum_{i=1}^{n} g_i \left( \dot{q}_i(t) \tilde{\phi}_{j,i} \right)
= g(f(x_j))
$$

Therefore, if a map exists such that a state $x_k$ can be mapped from the state $x_j$, then there exist a map from the delayed vector $\Phi(x_j)$ to the state $x_k$. In other words, provided that the observed state $x_j$ and the objective state $x_k$ are not null point nodes, then the objective state $x_k$ can be represented using a delayed vector constructed from the observations on $x_j$.

Consequently, one needs to ensure that the measurements are not taken at the null point of a dominant mode. In practice, that measurement should be taken at the maximum value of a node node if possible. For instance, in the case of cantilever-like civil structures, where masses are installed in series and separated by stiffness and dashpot elements, it is known that the response is dominated by the first few modes. Typically, an observation taken at the top floor would satisfy the requirements mentioned above. In the case of decentralized control, technical considerations such as data transmission range and wiring may constrain available measurements to local states that are physically located around the control device.

The next section describes the full SOI-WNN algorithm. It is followed by a demonstration of its performance using several examples of identification and control.

### 3.5 SOI-WNN Algorithm

Now that we have presented the SOI algorithm, we can join it to the WNN controller introduced Chapter 2. The SOI-WNN is our proposed novel
CHAPTER 3. ORGANIZING THE INPUT SPACE

intelligent controller. The algorithm is as follows:

1. Take the last $n$ observation of the local states $(\dot{x}_{i+1} - \dot{x}_i), (\ddot{x}_{i+1} - \ddot{x}_i), \dot{x}_i, u_i$, where $i$ and $i - 1$ correspond to the degrees of freedom of the two floors sandwiching the $i^{th}$ semi-active device.

2. Process the acceleration $\ddot{x}_i$ in the SOI algorithm to find the proper time delay $\tau$ and embedding dimension $d$, and adapt the required input delay parameters accordingly, as described in Section 3.4.2:
   
   2.1 Finds the appropriate time delay $\tau$ for constructing the local delay vector $\nu_q$. The parameter $\tau$ is selected using the mutual information method based on Shannon’s information theory. [50].
   
   2.2 Constructs a phase-space using $\tau$, and uses the false nearest neighbor method based on the algorithm presented in [86] for computing the embedding dimension $d$ to build $\nu_q$.
   
   2.3 Adapts the current input space smoothly based on the input vector $\nu(k)$. We point out that a smooth adaptation of $\nu(k)$ requires the adaptation to be done in the neighborhoods $[\tau(k) - 1, \tau(k) + 1]$ and $[d(k) - 1, d(k) + 1]$, as $x(\tau(k)) \approx x(\tau(k) \pm 1)$, and that the change of dimensionality of the representation be achieved smoothly. The first restriction greatly reduces the search space, thus computation time, and the second ensures robustness of the representation.

   2.3.1 If $d$ has changed, adapt the wavelet dimensions accordingly.

3. Construct the delay vector using observations $\ddot{x}_i$ and $u_i$.

4. Compute the SOI-WNN outputs based on the new inputs.

5. Send the force to the internal controller of the semi-active device, which in turn will compute an appropriate voltage$^1$:

   5.1 Find the adaptation region, as discussed in Section 2.4.1, using the last force input error $\tilde{u}$.
   
   5.2 Compensate the neural outputs with the sliding control component accordingly.

---

$^1$the internal controller for the proposed semi-active device will be discussed in the next section.
5.3 Send the required force to the semi-active device.

6. Compute the new force input error $\tilde{u}$.

7. Construct the new error vector using the local displacement and velocity measurements $x_i, x_{i+1}, \dot{x}_i, \dot{x}_{i+1}$. Note that the sliding surface weight matrix $P$ is built using equal and opposite weights at the degrees-of-freedom representing the floors sandwiching the semi-active devices. Thus, the error $e_i$ can be written
   \begin{align*}
e_i &= \lambda_x (x_{i+1} - x_i) + \lambda_\dot{x} (\dot{x}_{i+1} - \dot{x}_i),
   \end{align*}
   where $\lambda$ represents weights.

8. Establish if the dynamic system is in an impulse zone. If yes, flag that the SOI-WNN will need to forget the new rule.

9. Run the self-organizing mapping process. Add or prune nodes if needed, as indicated in Section 2.4.3.

10. Compute the smoothing function $m_c$, which is the sliding mode component based on $\tilde{u}$

11. Adapt the network using the adaptation rules, as indicated in Section 2.4.4.

### 3.6 Simulations

It is now time that we analyze the performance of the SOI-WNN, or the WNN using the SOI for an automated input selection. Despite that Chapter 5 is entirely devoted to simulations on a large-scale system, we need to first use simple simulations to help analyze and understand the performance of our novel controller. The simulations in this section are as follows:

1. Tracking of a function.

   First, we take a nonlinear dynamic system, and track a sinusoidal function. We use this simulation to explicitly switch from two different dynamics. It will help us demonstrating the capability of the SOI algorithm to adapt the black-box inputs to new dynamics. We will also take the opportunity to verify basic assumptions underlying the design of the SOI algorithm.
2. Regularization of a 3 DOF system.

Second, we expand from a 1 DOF to a 3 DOF system. We use the same structure as in Section 1.3.1. The structure is subjected to an harmonic excitation, and we verify the SOI-WNN performance using 1) active control; and 2) semi-active control. The objective of the active control is to demonstrate stability of the controller, while the semi-active control will show the performance of the controller for systems with limited force reachability.

3. Analysis of a chaotic excitation.

Third, we subject our 3 DOF to an earthquake. We illustrate, using RQA plots, that the SOI algorithm improves stationarity by focussing on local dynamics.


Fourth and lastly, we verify the performance of the SOI-WNN at step-ahead predictions. In the simulations, we conduct step-ahead predictions of three different earthquakes, a near-field, a mid-field, and a far-field excitation. Neuroprediction can be a useful tool for predictive control.

3.6.1 Tracking of a Function

We first simulate the SOI-WNN controller with the following nonlinear equation:

\[
 f(x, \dot{x}, u) = \left[1 - \left(\frac{(x - 0.1)^2}{0.1^2} + \frac{(\dot{x} - 0.05)^2}{0.05^2}\right)\right] e^{\left(-\frac{(x-0.1)^2}{0.1^2} + \frac{(\dot{x}-0.05)^2}{0.05^2}\right)} + u
\]

where the excitation input is \( x = 0.2 \sin 0.05t \), and the tracking objective is \( x^* = 0.02 \sin 0.01t \). We have selected this arbitrary example because of the stationarity of the excitation and reference signal, which lets nonstationarity arise from the black-box model only. In addition, the stationarity of both signals allows us to pre-process their time series using Takens theorem in order to determine fixed inputs that would appropriately represent their dynamics.

The WNN non-adaptive parameters are kept constant throughout the simulations, and no training is conducted a priori. The objective is to have the neurocontroller learn the control function as quickly as possible. The
3.6. SIMULATIONS

equation is sampled at 100 Hz, and a delay is induced in the controller using the following dynamics: \( \dot{u}_{\text{act}} = -20(u_{\text{act}} - u_{\text{req}}) \), where \( u_{\text{act}} \) is the actual force from the actuator, and \( u_{\text{req}} \) is the required force from the controller. A sliding window size of \( n = 100 \) time steps is selected. The SOI algorithm is compared against three cases of fixed inputs:

- An input vector built using \( \tau = 31 \) and \( d = 2 \), which are parameters obtained from pre-processing the time series of the excitation signal, without forcing (\( u = 0 \)).

- An input vector built using \( \tau = 8 \) and \( d = 2 \), which are parameters obtained from pre-processing the time series of the reference signal.

- An input vector built using \( \tau = 31 \) and \( d = 8 \), which are the optimal fixed input parameters obtained within the search space \( \tau = [1, 40] \) and \( d = [1, 10] \) while simulating the system with forcing.

Note that values obtained for \( \tau \) are coincidentally the same for the first and third case, and that a dimension of 2 was expected for the first and second case due to the low complexity of both signals. The large embedding dimension for the third scenario can be explained by a more complex phase-space that counts several crossings once the system (3.42) includes the forcing \( u \).

Fig. 3.21 shows the time series response of the SOI algorithm versus the optimal fixed parameters. The SOI algorithm gives a quicker convergence and better control results. This is due to the dynamics of the control rule changing with time, for which adapting the input space results in a better function representation, as hypothesized. Table 3.1 shows the RMS error for the four input cases over a control time of 20 seconds. Results from the overall time series show that the SOI gives good performance relative to the fixed input cases. The RMS error taken after 5 seconds indicates that its convergence is significantly better. Note that the error threshold of the neurocontroller is set to \( 10 \times 10^{-5} \). Fig. 3.22 shows the evolution of the input vector parameters with time.

Table 3.1: RMS error of the controller over various input strategies (\( \times 10^{-5} \))

<table>
<thead>
<tr>
<th>( \tau = 31 )</th>
<th>( \tau = 8 )</th>
<th>( \tau = 31 )</th>
</tr>
</thead>
<tbody>
<tr>
<td>SOI</td>
<td>( d = 2 )</td>
<td>( d = 2 )</td>
</tr>
<tr>
<td>over all series</td>
<td>18.8</td>
<td>21.4</td>
</tr>
<tr>
<td>after 5 seconds</td>
<td>2.93</td>
<td>13.2</td>
</tr>
</tbody>
</table>
The SOI algorithm is built under the assumption of quasi-stationarity of local maps \( q \) created by the sliding window. Thus, we first verify the performance of the algorithm as a function of the sliding window size \( n \). Fig. 3.23 shows the RMS error after 5 seconds for various values of \( n \). The performance of the algorithm remains approximately constant for values greater than 50 time steps, with a slight degradation for larger window sizes. Note that a large window size negatively influences computation speed.

We now verify the main assumption of quasi-stationarity of local maps. A time-series stationarity index is constructed by determining the change in the control rule within a map. If the change is minimal, then we can write (3.6) in a stationary way using \( u(k, t) \approx u(k) + T \), where \( T \) is a periodicity in the input, so that \( u(k + 1) \approx g(y, u) \). We take observations at step \( k \), and obtain the control force using the control rule at step \( k - n \). The stationarity index is built comparing \( u(k - n) \) and \( u(k) \), and counts the number of local maps that remained under a given percentage change threshold. Fig. 3.24 graphs the stationarity index over various time ranges. The figure shows the number...
of stationary maps as a function of the percentage of change allowed between \( u(k - n) \) and \( u(k) \). Results show that 43\% of the maps have a change less than 5\% over the entire simulation (last 20 seconds), which increases to 88\% for the last 1 second. If a change of 10\% is allowed, 64\% of maps show to be quasi-stationary over the entire simulation, and 91\% over the last 5 seconds. Results show that the level of quasi-stationarity increases significantly with the convergence of the black-box model. We estimate that levels of stationary maps above 85\% under 10\% allowable change satisfy quasi-stationarity, which is met for the last 10 seconds of the simulation.

Lastly, we switch off the SOI algorithm once the error metric stays below a threshold for a pre-defined number of step, in order to identify static inputs for the representation once the system has converged. For the task, the capacity of the network to prune nodes has been relaxed, as we expect to need a denser network to construct an accurate representation of the global dynamics. Fig. 3.25 shows the evolution of the input parameters over time. The inputs become static after 20 seconds, identifying the parameters \( \tau = 12 \) and \( d = 2 \). This compares well with the pre-processed values of the controlled time-series aforementioned to be \( \tau = 8 \) and \( d = 2 \), as the phase-space of the sinusoidal target only marginally unfolds. The value for \( d \) is significantly lower than for the optimal fixed inputs strategy \( (d = 8) \), because the SOI

![Figure 3.22: Evolution of \( \tau \) and \( d \) for the dynamic inputs.](image-url)
CHAPTER 3. ORGANIZING THE INPUT SPACE

Figure 3.23: RMS error of the SOI algorithm for various sliding window sizes.

The SOI algorithm computes the optimal $d$ based on the last $n$ observations only.

### 3.6.2 Regularization of a 3 DOF System

Secondly, we take the 3 DOF system utilized in Section 1.3.1 and subject it to an harmonic excitation acting on the fundamental frequency: $10 \sin 34.5t$. We start by demonstrating stability of the SOI-WNN in the context of active controller. Afterwards, we will replace the actuator by a semi-active device, and show that the SOI-WNN controller can effectively stabilize a system with limited force reachability.

The SOI algorithm utilizes the first floor acceleration $\ddot{x}_1$ to update values of $\tau$ and $d$. The embedding vector is constructed utilizing $\ddot{x}_1$ along with the control force $u$. The mitigation objective is the 3rd floor displacement $x_3$, and the sampling rate is 250 Hz.

**Active Control**

We start by equipping the 3 DOF system with an actuator between the ground and the first floor.

Fig. 3.26a shows the time series of the 3rd floor displacement for the
uncontrolled and controlled case. The neurocontroller achieves mitigation to the required level of error. Fig. 3.26b shows the evolution of the embedding vector parameters $\tau$ and $d$. Fig. 3.26c demonstrates that the control weights converge. Fig. 3.26d compares the mitigation results of the SOI algorithm against a WNN with an optimized and constant delay vector. The convergence to the error bound is similar. The slightly quicker performance of the constant delay vector case is explained by the stationarity of the excitation.

**Semi-Active Control**

The next step is to simulate the structure with a semi-active control device. The semi-active device is the MFD, which will be presented in the next chapter. We have not yet explicitly discussed the dynamic of the MFD, but its performance is not the main focus of this simulation. The device could be
Figure 3.25: Identification of static $\tau$ and $d$ for a global representation.

any semi-active damper incapable of adding energy to the controlled system.

Fig. 3.27a shows the time series of the 3rd floor displacement for the uncontrolled and controlled case. The neurocontroller achieves mitigation to the required level of error, but does not remain fully within the bounds as in Fig. 3.27a. This is explained by the learning being almost negligible around the error bound as a consequence of the sliding controller. Fig. 3.27b shows the evolution of the embedding vector parameters $\tau$ and $d$. Fig. 3.27c demonstrates that the control weights converge. Fig. 3.27d compares the mitigation results of the SOI algorithm against a WNN with a constant delay vector. The convergence to the error bound is similar. The slightly quicker performance of the constant delay vector case might be explained by the stationarity of the excitation.

### 3.6.3 Analysis of a Chaotic Excitation

The El Centro 1940 North-South component earthquake is used as the chaotic excitation. Note that it is scaled by a factor of 5 to match the dynamics of the model. The control performance criterion is inter-story displacement for damage attenuation. Fig. 3.28a shows the maximum inter-story displacement for various control strategies and delayed vectors. The passive-on and passive-
3.6. SIMULATIONS

Figure 3.26: 3 DOF system controlled by an active system. a) Uncontrolled versus controlled case; b) Evolution of the embedding vector properties; c) Convergence of weights. Vertical lines indicate a node pruning; and d) Comparison with a pre-selected delay vector.

off cases refer to the semi-active damper used with maximum voltage always on and no voltage respectively. It is observed that the SOI-WNN gives excellent mitigation performance, and is capable of achieving the same result as for the pre-processed inputs case. Fig. 3.28b shows the network size evolution for different delayed vectors. The SOI algorithm keeps a minimal network size. The evolution of the delayed vector is depicted in Fig. 3.29. Note that the pre-processed inputs resulted in a time delay of 9 and a embedding dimension of 5.
In order to analyze the capability of the SOI algorithm of adapting to local dynamics, it is useful to look at the input $\ddot{x}_1$, the first floor acceleration, which is the input directly used in the SOI algorithm. Fig. 3.30 shows the time series of $\ddot{x}_1$ along with the recurrence map of the delay vector constructed using the values of $\tau$ and $d$ obtained from pre-processing the data. In Fig. 3.30b, a black dot indicates a pattern recurrence within a radius of 5% of the maximum delay vector norm $\|\mathbf{v}\|_{\text{max}}$. The numerous white stripes seen in Fig. 3.30b show that the signal is nonstationary. Consequently, the delay vector...
3.6. SIMULATIONS

Figure 3.28: Performance of the SOI-WNN controller. a) Maximum inter-story displacements for various control strategies; and b) Comparison of network size for different delayed vectors.

constructed with the global signal is not efficient at localizing patterns in the phase space.

The next step is to investigate whether the dynamic delay vector can properly find patterns in local dynamics. It would be rather useless and

Figure 3.29: Evolution of the delayed vector: a) time delay; b) embedding dimension.
CHAPTER 3. ORGANIZING THE INPUT SPACE

Figure 3.30: a) Time series of $\dot{x}$; and b) the recurrence map for the pre-processed values of $\tau$ and $d$ ($\tau = 9$ and $d = 5$).

certainly time-consuming to discretize the time series at each steps when $\tau$ or $d$ is updated and plot a recurrence map to analyze patterns. Instead, the time series is discretized in three general sections and the average of $\tau$ and $d$ utilized to study the delay vector locally. If results look satisfying, then it can be deduced that further discretization would lead to similar, if not better, results. Fig. 3.31 shows a discretization of the time series in three subsets and the evolution of both $\tau$ and $d$. The dashed rectangles denote discrete subsets.

Fig. 3.32 shows the local recurrence maps using the global values for $\tau$ and $d$ to construct the delay vector. Fig. 3.33 shows the local recurrence maps using the average local values for $\tau$ and $d$ from the SOI algorithm to construct the delay vector. All maps are built with a recurrence of 5% radius relative to the maximum norm of the local delay vector. It can be observed that nonstationarity (sparsity of patterns in the recurrence map) is significantly reduced using the SOI algorithm. Moreover, some patterns seems to be more distinguishable in the recurrence maps from Fig. 3.33. Those patterns are easily observed in Fig. 3.33c versus Fig. 3.32c. Thus, one can conclude that the SOI algorithm is efficient at finding local patterns in local dynamics.
3.6. SIMULATIONS

Figure 3.31: Discretization of the time series.

Figure 3.32: Local recurrence maps using the global values for $\tau$ and $d$.

Figure 3.33: Local recurrence maps using the average local values for $\tau$ and $d$ from the SOI algorithm: a) $\tau = 33$ and $d = 3$, b) $\tau = 28$ and $d = 4$; and c) $\tau = 18$ and $d = 5$. 
3.6.4 Neuroprediction

Step-ahead prediction of an earthquake involves the very complex and non-trivial problem of identifying a chaotic time series, sequentially and online. For the simulations, the WNN is required to conduct step-ahead predictions for three different earthquake time series. The earthquakes consists of the San Fernando 1971 North-South component (near-field), El Centro 1940 North-South component (mid-field), and Mexico City 1965 North-South component (far-field). The level of stationarity of the earthquake time series decreases with the distance of the earthquake center. Hence, the far-field earthquake is very nonstationary with bigger impulses. Once again, we insist that the adaptive model is not trained a priori, and predictions are achieved with no prior knowledge using sequential online adaptation. All non-adaptive parameters are set constant for all simulations for ease of comparison, which is allowed by scaling all excitations to the same maximum value, except for the size of the sliding window which changes with the nature of the excitations. The window is set to a value of \( n = 50 \) for the near-field earthquake to account for highly varying local dynamics, while it is expended to \( n = 100 \) for the mid-field earthquake and \( n = 200 \) for the far-field earthquake.

Results using a dynamic input space (SOI algorithm) are compared against three fixed input space strategies. First, we pre-process the full time series for constructing \( \nu \) using the same parameters for establishing \( \tau \) and \( d \) taken for the algorithm. Second, we take a small delay in a small embedding dimension. Lastly, we take \( \tau \) and overembed it. We perform short-term step-ahead predictions (1 to 15 steps) and compare the performance of strategies using the error metric: \( 1 - \left( \frac{\sqrt{\sum (y - \hat{y})^2}}{\sqrt{\sum y^2}} \right) \), where \( y \) is the earthquake signal, and \( \hat{y} \) is the prediction. The error metric represents the % forecasted with respect to the benchmark "no prediction". Fig. 3.34 shows the predictive performance for the earthquakes. We first remark that the overall forecasting capabilities increases with the decreasing level of nonstationarity of the earthquakes, as one would expect. The performance of the predictive WNN is poor for the San Fernando earthquake, but still gives a positive forecasting value. The performance of the SOI is comparable to the performance with the short delay fixed input case, except for the Mexico city earthquake, where the SOI is clearly better, but performs similarly to the pre-processed case on average. For all three cases, the dynamic inputs (SOI) succeeds at giving the best results. Table 5.9 summarizes different values for \( \tau \) and \( d \) for the earthquakes.
3.6. SIMULATIONS

Figure 3.34: Earthquake step-ahead predictions. a) San Fernando 1971; b) El Centro 1940; and c) Mexico City 1965.

Table 3.2: Average delay vector parameters.

<table>
<thead>
<tr>
<th></th>
<th>San Fernando</th>
<th>El Centro</th>
<th>Mexico City</th>
</tr>
</thead>
<tbody>
<tr>
<td>dynamic inputs</td>
<td>( \tau = 6.2; d = 3.0 )</td>
<td>( \tau = 8.9; d = 2.5 )</td>
<td>( \tau = 16.4; d = 2.3 )</td>
</tr>
<tr>
<td>pre-processed</td>
<td>( \tau = 7; d = 4 )</td>
<td>( \tau = 11; d = 7 )</td>
<td>( \tau = 27; d = 6 )</td>
</tr>
<tr>
<td>short delay</td>
<td>( \tau = 5; d = 2 )</td>
<td>( \tau = 5; d = 2 )</td>
<td>( \tau = 5; d = 2 )</td>
</tr>
<tr>
<td>overembedding</td>
<td>( \tau = 7; d = 10 )</td>
<td>( \tau = 11; d = 10 )</td>
<td>( \tau = 27; d = 10 )</td>
</tr>
</tbody>
</table>
CHAPTER 3. ORGANIZING THE INPUT SPACE

3.7 Conclusion

In this chapter, we have discussed the problem of organizing the input space. We have provided the reader with some theory on nonlinear time series analysis, and discussed various input selection strategies, with a special emphasis on Taken’s Embedding Theorem. Subsequently, we have introduced the SOI algorithm, which is the main contribution of the chapter. The SOI algorithm is a strategy designed to automate the input selection for adaptive black-box representations. This selection is done sequentially and online. Potential applications of the SOI algorithm include automation of the input space design process, and control with local or limited state measurements.

Furthermore, we have incorporated the SOI algorithm with the WNN controller presented in the previous chapter giving rise to the SOI-WNN. After listing the SOI-WNN algorithm, we have demonstrated the performance of the SOI-WNN algorithm for tracking and regulatory control problems, as well as for step-ahead prediction. We have observed that the SOI-WNN is a very efficient way of controlling systems with limited state measurements, and that is could also effectively be used for system identification or step-ahead predictions. In one of the simulations, we have used the MFD as a semi-active control device. It is now time to introduce that novel damping device, which is the central theme of the next chapter.
4

Control Devices for Large-Scale Structures
CHAPTER 4. CONTROL DEVICES FOR LARGE-SCALE STRUCTURES

Chapter Notation

\begin{align*}
\alpha, \beta, \eta, \xi & \quad \text{constants} \\
\Delta t & \quad \text{time step} \\
\mu & \quad \text{friction coefficient} \\
\omega & \quad \text{angular velocity} \\
\phi & \quad \text{angle} \\
\sigma_0, \sigma_1, \sigma_2 & \quad \text{constants} \\
\tau_f & \quad \text{frictional torque} \\
\theta & \quad \text{shoe angle} \\
a, b & \quad \text{distances} \\
b_w & \quad \text{shoe width} \\
c_{\text{mfd}} & \quad \text{MFD damping coefficient} \\
f & \quad \text{force} \\
g & \quad \text{Striebeck effect} \\
k_{\text{mfd}} & \quad \text{MFD stiffness coefficient} \\
p & \quad \text{pressure} \\
p_{\text{avg}} & \quad \text{average pressure} \\
p_{\text{max}} & \quad \text{maximum pressure} \\
p_{\text{tot}} & \quad \text{total pressure} \\
r & \quad \text{radius} \\
s & \quad \text{sliding surface} \\
x_s & \quad \text{constant} \\
v_{\text{act}} & \quad \text{actual voltage} \\
v_{\text{req}} & \quad \text{required voltage} \\
w_m & \quad \text{material mass} \\
z & \quad \text{evolutionary variable} \\
C & \quad \text{force amplification factor} \\
F & \quad \text{force} \\
F_C & \quad \text{Coulomb force} \\
F_{\text{act}} & \quad \text{actual force} \\
F_{\text{C,0}} & \quad \text{nominal Coulomb force} \\
F_{\text{C,max}} & \quad \text{maximum Coulomb force} \\
F_{\text{friction}} & \quad \text{friction force} \\
F_{\text{req}} & \quad \text{required force} \\
F_s & \quad \text{Striebeck force} \\
N & \quad \text{normal force} \\
P_f & \quad \text{frictional power} \\
R_{\text{link}}, R_x, R_y & \quad \text{reactions} \\
U_f & \quad \text{break work} \\
V & \quad \text{Lyapunov function} \\
W & \quad \text{actuation force}
\end{align*}

4.1 Introduction

In the last two chapters, we have visited the realm of control algorithms and proposed a new controller for unknown systems with limited state measurements. We are now introducing in this chapter a novel semi-active control device, to be used along the controller in an integrated closed-loop control system. The device, the Modified Friction Device (MFD), is novel by its high damping force reachability for a low power requirement, achieved with reliable mechanical technologies. Before further discussing the MFD, we would like to briefly introduced state-of-the-art control devices that have been...
used or proposed for civil structures. Most devices that we can find in the literature have been developed to enhance performance of structural systems [175]. Housner et al. [68] made an extensive review of different structural control techniques; their paper should be considered as a good start for a novice in the field.

Structural control devices can be divided into three categories: passive, active and semi-active devices. Passive control refers to the use of mechanical devices that do not require energy input; they are usually energy dissipation devices. These systems are widely accepted in the engineering field. Symans et al. [182] provides a state-of-the-art review of the commonly used passive control systems for seismic protection; they are summarized in Table 4.1. Despite their ease of implementation, passive strategies are generally only applicable to limited bandwidths of excitation and do not perform well against near-field earthquakes due to the nature of the impact that comes in the form of a shock rather than an energy build-up [6, 212, 62]. Near-field earthquakes are characterized by a high peak acceleration, a long velocity pulse period and a large displacement.

Active systems, conversely to passive schemes, require energy to operate, and they typically are capable of better mitigation performance. However, they are not widely used in structural engineering. Factors impeding their application are as follows [216, 189, 204]:

- The actuators require a significant amount of power to operate, which is unlikely to be deliverable during an earthquake, affecting their reliability.

- Robustness is a significant concern as, by adding energy to the controlled system which is typically anchored to the ground (cantilevered), active schemes can destabilize structures.

- Actuator saturation may lead to serious consequences, such as structural destabilization, significant acceleration input, and mechanical damages.

Semi-active systems are characterized by a low energy demand and a control performance close to the active control schemes. Despite their early introduction in the 1920s for vehicle shock absorbers, they seem to have been proposed to structural engineering only in 1983, by Hrovat [70]. They have since attracted a lot of attention in research [174]. Due to their controllability and ability to operate at low voltage, semi-active devices rapidly became accepted by the structural control community.
CHAPTER 4. CONTROL DEVICES FOR LARGE-SCALE STRUCTURES

Table 4.1: Passive energy dissipation systems [182].

<table>
<thead>
<tr>
<th>Viscous Fluid Damper</th>
<th>Viscoelastic Solid Damper</th>
<th>Metallic Damper</th>
<th>Friction Damper</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Basic Construction</strong></td>
<td><img src="image1" alt="Viscous Fluid Damper" /></td>
<td><img src="image2" alt="Viscoelastic Solid Damper" /></td>
<td><img src="image3" alt="Metallic Damper" /></td>
</tr>
<tr>
<td><strong>Idealized Physical Model</strong></td>
<td><img src="image5" alt="Force vs Displ." /></td>
<td><img src="image6" alt="Force vs Displ." /></td>
<td><img src="image7" alt="Force vs Displ." /></td>
</tr>
<tr>
<td><strong>Advantages</strong></td>
<td>- Activated at low displacements</td>
<td>- Activated at low displacements</td>
<td>- Stable hysteretic behavior</td>
</tr>
<tr>
<td></td>
<td>- Minimal restoring force</td>
<td>- Provides restoring force</td>
<td>- Long-term reliability</td>
</tr>
<tr>
<td></td>
<td>- For linear damper, modeling of damper is simplified.</td>
<td>- Linear behavior, therefore simplified modeling of damper</td>
<td>- Insensitivity to ambient temperature</td>
</tr>
<tr>
<td></td>
<td>- Properties largely frequency and temperature-independent</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>- Proven record of performance in military applications</td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Disadvantages</strong></td>
<td>- Possible fluid seal leakage (reliability concern)</td>
<td>- Limited deformation capacity</td>
<td>- Device damaged after earthquake; may require replacement</td>
</tr>
<tr>
<td></td>
<td></td>
<td>- Properties are frequency and temperature-dependent</td>
<td>- Nonlinear behavior; may require nonlinear analysis</td>
</tr>
<tr>
<td></td>
<td></td>
<td>- Possible debonding and tearing of VE material (reliability concern)</td>
<td></td>
</tr>
</tbody>
</table>
4.2 Semi-Active Systems

Semi-active mechanical devices are categorized in four main families:

- variable orifices
- controllable fluids
- variable stiffnesses
- variable frictions

Here, we shortly describe those four types of devices. The reader will see later that the proposed MFD is a variable friction device, but actually mimicking the dynamics of controllable fluids.

4.2.1 Variable Orifices

Variable orifice dampers are composed of a cylinder-piston system with a by-pass pipe connected at both end. The semi-active system is illustrated in Fig. 4.1. The by-pass pipe has a valve that can be opened or closed. In closed position, the device behaves like a stiffness element. In open position, it will behave like a damper, where the area of the orifice will control the fluid flow and set damping properties. It is thus a binary damping device. The first large-scale application of a variable orifice damper in the US was achieved on the Walnut Creek Bridge on interstate highway I-35. The application is illustrated in Fig. 4.2.

Variable orifice dampers can be used acting as an on/off switch for braces, termed active variable stiffness (AVS). An example of application is in the Kajima Technical Research Institute. Fig. 4.3a shows the structure equipped with the AVS system. Fig. 4.3b is a close-up on the actual AVS system. Figs. 4.3c and 4.3d illustrate the lock/unlock position of the mechanism.
CHAPTER 4. CONTROL DEVICES FOR LARGE-SCALE STRUCTURES

Figure 4.1: a) Variable orifice damper [183]; and b) its simplified schematic [6].

Using the AVS idea, Agrawal and Yang [6] introduced a semi-active stiffness damper (SASD). The idea of the control scheme is to store potential energy and release it when this energy is maximum [197]. Agrawal and Yang [6] studied the efficiency of this strategy for a base-isolated structure subjected to a near-field earthquake. Yang et al. [214] verified the SASD theory on a full-scale model. Wongprasert and Symans [204] used these variable orifice dampers for a numerical evaluation of a structure base-isolated with a friction pendulum system bearing, and with a low-damping rubber bearing.

Figure 4.2: First large-scale application of a variable orifice damper in the US [177]. a) Installation; and b) variable orifice damper.
4.2. SEMI-ACTIVE SYSTEMS

Figure 4.3: Kajima Technical Research Institute AVS system. a) Structure with braces; b) close-up on the AVS system; c) illustration of the system in its locked position; and d) illustration of the system in its unlocked position (courtesy of Kajima Technical Research Institute).

4.2.2 Controllable Fluids

Controllable fluid dampers use rheological fluid, a fluid whose particle align upon the application of an electric or magnetic field, which changes the viscosity of the fluid. Two types of controllable fluid dampers exist: electrorheological (ER) dampers and magnetorheological (MR) dampers. ER dampers differ from MR dampers by applying an electric field rather than a magnetic field to the fluid, and the magnetic-based rheological fluid is much more robust to temperature effects and impurities. It results that MR dampers are preferred over ER dampers for civil engineering applications.
CHAPTER 4. CONTROL DEVICES FOR LARGE-SCALE STRUCTURES

Table 4.2: Technical characteristics of a 200 kN MR damper [212].

<table>
<thead>
<tr>
<th>Characteristic</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Stroke</td>
<td>± 8 cm</td>
</tr>
<tr>
<td>$F_{\text{max}}/F_{\text{min}}$</td>
<td>10.1 at 10 cm/s</td>
</tr>
<tr>
<td>Cylinder bore (internal diameter)</td>
<td>20.32 cm</td>
</tr>
<tr>
<td>Maximum input power</td>
<td>&lt; 50 W</td>
</tr>
<tr>
<td>Maximum force (nominal)</td>
<td>200 kN</td>
</tr>
<tr>
<td>Effective axial pole length</td>
<td>8.4 cm</td>
</tr>
<tr>
<td>Coils</td>
<td>$3 \times 1050$ turns</td>
</tr>
<tr>
<td>Apparent fluid viscosity</td>
<td>1.3 Pa·s</td>
</tr>
<tr>
<td>Fluid maximum yield stress</td>
<td>62 kPa</td>
</tr>
<tr>
<td>Gap</td>
<td>2 mm</td>
</tr>
<tr>
<td>Active fluid volume</td>
<td>$\sim 90$ cm$^2$</td>
</tr>
<tr>
<td>Wire</td>
<td>16 gauge</td>
</tr>
<tr>
<td>Inductance</td>
<td>$\sim 6.6$ henries</td>
</tr>
<tr>
<td>Coil resistance</td>
<td>$3 \times 7.3$ ohms</td>
</tr>
</tbody>
</table>

because magnetic fields require less power. Research in the application of MR dampers to civil engineering has received significant attention.

The rheological fluid contained within MR dampers comprises polarizable and magnetizable particles that line up upon magnetic excitation, causing a change in the liquid’s viscosity within a few milliseconds [207]. For a large-scale 200 kN MR damper, this response would be on the order of 60 milliseconds. Their low power requirement, which is 50 W for a 200 kN damping force [211], also makes them very attractive as only a battery is needed to drive their response, which could easily be provided as a secondary power source in case of power failure. Table 4.2 shows the typical properties of a 200 kN MR damper. Fig. 4.4 is a picture of a 200 kN MR damper. MR dampers are also characterized by their fail safe property. In the event of an electrical problem, the device behaves like a passive viscous damper. The 200 kN MR damper has been widely studied. Recently, a 500 kN capacity has been designed and fabricated [120]. Also, it has been suggested that 1000 kN capacities could be theoretically fabricated [82].

Some models have been proposed over the years for modeling the MR damper behaviors. Mathematical models can be divided into static and dynamic models. The Bouc-Wen model is the simplest one used to model the liquid hysteresis. It consists of a stiffness, a dashpot, and a Bouc-Wen
4.2. SEMI-ACTIVE SYSTEMS

Figure 4.4: 200 kN MR damper.

element in parallel, as shown in Fig. 4.5. More complex mathematical models have been proposed, such as the celebrated phenomenological model [176], which successfully models the stiction phenomena and shear thinning effect. Recent research has also been made on non-mathematical models due to the complexity in mapping the required voltage for a desired force [103], such as adaptive identification, in order to map the relationship between the necessary voltages for desired forces [188]. Nevertheless, a saturation-type control rule for the voltage selection, which consists of applying full current in the MR damper if the magnitude of the required force is higher in absolute value than and of the same sign of the magnitude of the damper force, and applying zero current otherwise, has shown excellent performance and simplicity [76, 219].

In civil engineering applications, MR dampers have been applied to stay cables vibration mitigation [207] and in building braces [177], and have also been suggested for numerous hybrid schemes. MR dampers have also been used in special applications such as ship lift tower [191], and offshore platform [205]. Note that most of their applications are in vehicle suspension systems.

4.2.3 Variable Stiffnesses

Despite described previously in the context of an hybrid scheme with variable orifice dampers, active variable stiffness (AVS) can be their own class of semi-active damping. While the variable orifice dampers generally act as a switch on/off, other methods have been proposed that suggest a higher controllability. Narasimhan and Nagarajaiah [135] proposed a semi-active variable stiffness
system (SAIVS) where the stiffness can be varied continuously. Such system is represented in Fig. 4.6. This schematic is for a uniaxial control along the \( x \) direction. Joint 1 is free to move along the \( y \) direction while joint 2 is free to move in any direction, but its rail is attached to a slab. Joints 3 and 4 are free to move along the \( x \) direction and their rails attached to the ground. Thus, by moving joint 1, the equivalent force along the \( x \) direction is 
\[
    f_x = (k_e \cos^2 \theta) \Delta y.
\]
The performance of the proposed system has been shown to be promising.

Walsh \textit{et al.} [197] presented a variable amplification device (VAD). VAD are comparable to standard automobile transmission. The system is represented in Fig. 4.7. In the figure, the floor is connected to the stiffness element via a set of gears. Depending on which gears are engaged, a different amplification of the floor displacement will be transmitted to the spring element.

### 4.2.4 Variable Frictions

The last category is the variable friction devices. They consist of mechanisms that dissipate energy via controllable friction forces.

Kannan \textit{et al.} [84] introduced a variable friction damper that uses an hydraulic actuator. The main disadvantage of hydraulic actuators is in their
4.2. SEMI-ACTIVE SYSTEMS

Figure 4.6: SAIVS [135].

Figure 4.7: VAD; \( r \) is the gear radius [197].
CHAPTER 4. CONTROL DEVICES FOR LARGE-SCALE STRUCTURES

delay in reaching the actuation force \[106\]. For convenience, the field has introduced two other types of variable friction dampers capable of large frictional forces.

The first one is the electromagnetic friction damper, proposed by Agrawal & Yang \[6\]. The authors utilized the friction device for control of base-isolated buildings. The semi-active scheme consists of a friction pad installed between two steel plates. The normal force \( N \) is varied by changing the electric current in solenoids located at the outer surface. The device is capable of a force in the order of 20 kN. The electromagnetic friction damper has also been used for an engine mount in \[115\].

The second type is the piezoelectric friction device presented by Gaul \textit{et al.} \[52\]. It consists of two friction surfaces mounted on a piezoelectric stack actuator. The piezoelectric stack is activated to control the normal force on the friction surfaces. That type of variable friction device has been used as a friction joint for space truss structures \[53\]. Durmaz \textit{et al.} \[44\] developed a high-capacity friction damper by extending the concept to larger contact areas. The semi-active damper has a force range of 0.890 kN to 11 kN. It is worth mentioning that \[23\] developed a variable friction device inspired by car braking systems, but the device also uses piezoelectric actuators and is limited to lightweight mechanical structures. Fig. 4.8a shows an electromagnetic friction damper, Fig. 4.8b shows the variable friction damper proposed in \[6\], and Fig. 4.8c shows a typical piezoelectric friction damper.

In large-scale applications, Gu & Oyadiji \[156\] investigated the performance of variable friction dampers on a wind-excited truss tower. Also, Chen & Chen \[32\] experimentally studied a variable friction damper made from piezoelectric actuators. The damper had a capacity of 800 N and operated in the range of 0 to 1000 V. Xu \[210\] also studied a similar friction damper, but with a capacity in the range of 5 to 340 N for an input voltage from 0 to 150 V. To the best knowledge of the authors, the largest capacity of a variable friction damper was reported in \[227\], and was of 3 kN for an input in the range of 0 to 120 V.

4.3 Hybrid Systems

Like semi-active devices, hybrid systems are used for an enhanced controllability using minimum voltage. Several hybrid control scheme have been proposed in the literature. They are typically composed of passive dissipation
4.3. HYBRID SYSTEMS

Figure 4.8: a) Electromagnetic friction damper [115]; b) SAEMFD [6]; and c) piezoelectric friction damper [142].

systems coupled with active or semi-active devices. Among those, active tuned-mass dampers (ATMDs) and active mass-drivers (AMD) are the most widely accepted control systems for civil structures [11]. ATMDs have been proposed by Lund [118], and since widely studied [119, 28, 8]. They can be found in a variety of applications [40]. They consist of a tuned-mass damper (TMD) or a mass on rollers installed in series with an actuator. Their first large-scale application was conducted on the Kyobashi Seiwa Building [74]. Fig. 4.9a shows the structure. Fig. 4.9b schematized the AMD system components installed in the structure. Fig. 4.9c illustrates the AMD system.
A weight is driven by an actuator controlled by a ground motion feedback rule. Semi-active TMDs (STMDs) have also been proposed, but their physical applications are very recent. The first type of STMD to have been studied is the ER-TMD system [1, 64]. More recently, MR-TMD schemes have been researched [93, 92, 25, 111], and the first application of an MR-TMD has been documented in [223, 224]. It is installed in a tall building located in Santiago, Chile. Fig. 4.10 shows the building along with its two TMDs (the MR damper is not shown). In addition to ER- and MR-TMD, semi-active tuned-liquid column dampers have been studied [87], as well as SAIVS-TMD systems [134]. Lin et al. [109] proposed a STMD equipped with a variable friction damper.

Furthermore, hybrid base-isolated systems have been investigated. They mainly consist of a passive base isolation coupled with an active or semi-active device. The main advantage of such system is to decrease displacement between the ground and the structure. However, it comes to the expense of larger inter-story displacements. Examples of hybrid systems include variable-orifice base isolation systems [204], and MR base-isolated structures [100, 165, 116]. The first large-scale application of an MR-base isolation was achieved in Japan using a 400 kN MR damper [51]. Fig. 4.11a is a picture of the controlled structure. Fig. 4.11b shows the 400 kN MR damper. Lu et al. [117] proposed a base isolated system with a controllable stiffness device. The hybrid system, termed the stiffness controllable isolation system (SCIS), consists of a passive base-isolated system coupled with a variable friction device. Fig. 4.12 illustrates the mechanism.

Other variants of hybrid systems have been suggested. Ribakov & Gluck [157] proposed a control stiffness device (CSD) with MR dampers connected to amplifying braces at each floor levels and a base isolation system only equipped with CSD, illustrated in Fig. 4.13.

Shook et al. [167] proposed a hybrid system composed of MR dampers, elastomeric bearings (EB), smart memory alloys (SMA), and Friction-Pendulum Bearings. All of those components were installed in a semi-active base-isolation system, with SMA wires and MR dampers being used as additional restoring force mechanisms. Fig. 4.14 illustrates the hybrid system.
4.3. HYBRID SYSTEMS

Figure 4.9: Large-scale application of an AMD to the Kyobashi Seiwa Building. a) Picture of the structure; b) schematic of the installation; and c) control diagram (courtesy of Kajima Technical Research Institute).
CHAPTER 4. CONTROL DEVICES FOR LARGE-SCALE STRUCTURES

Figure 4.10: Structural equipped with the MR-TMD (MR damper not shown) [223].

Figure 4.11: Large-scale application of an MR-base isolation system. a) Picture of the structure; and b) 400 kN MR damper [177].
4.4 Modified Friction Device

Magnetorheological (MR) dampers have received considerable attention over the last decades because of their significant low power requirement, large resistance force, and fail-safe nature, but their applications to civil structures...
Figure 4.14: Configuration of MR, SMA, and FPB devices. [167].

is still in its infancy [95]. Some chemical issues specific to rheological fluids might impede the implementation of those devices in civil structures, such as sedimentation, which happens if the damper is not used for a long period of time [14]. Moreover, MR dampers may exhibit fluid leakage around the seal. The integrity of their seal is currently guaranteed on vehicle suspension systems for a life of 100,000 miles [30], but there is no indication in the literature on how well the seal can behave over the design period of a civil structure.

The implementation of semi-active devices in civil structures is partly impeded by mechanical obstacles. Those include fluid and mechanical parts reliability, dependability on an external power source and electronics, performance degradation over long period of time, and damping capacity. This thesis proposes a novel mechanically reliable damping device for large-scale structures that overcomes most of those practical obstacles to implementation, with the objective to enhance the applicability of semi-active damping systems to large-scale structures. The device, here termed the modified friction device (MFD), is inspired by the dynamic behavior of MR dampers and consists of a friction mechanism installed in parallel with a viscous and a stiffness element. The friction device is a rotating drum on which a variable friction can be
smoothly applied. The MFD is novel by its capability of very large damping forces, on the order of 200 kN, while operating on 12-volts batteries. This is a major improvement compared to existing variable friction schemes proposed in the literature. For instance, piezoelectric variable friction dampers have recently been experimented [32, 210, 227], but to the best knowledge of our knowledge, the largest damping capacity for battery-operated variable friction was in the range of $10^4$ N, reported in [212]. The significant difference in the theoretical high operating range arises from the self-energizing capacity of the braking mechanism, which greatly amplifies the frictional force. The MFD is based on current reliable and robust mechanical technologies, and is thus a mechanically reliable and robust semi-active device. Chapter 5 includes an extensive simulation of the device without the proposed controller. The reader will find the first published studied on the MFD in [112], where the nonlinearity of the MFD for control of an STMD is investigated versus a linear variable orifice device.

### 4.4.1 Device Dynamics

The proposed MFD consists of a stiffness, a viscous, and a controllable friction element installed in parallel, as schematized in Fig. 4.15a), where $x$ represents the device displacement and $F$ the reaction force. The variable spring in the variable friction element depicts a variable braking force. The controllable friction element differs from the other variable friction types by using a reliable mechanical system analogous to the braking system of a vehicle. It is also novel by the incorporation of both a stiffness and a viscous element, which provides minimal damping when the current is switched off or in the unfortunate failure of the friction element, also termed fail-safe mechanism. The objective of the device is to develop a force capable of controlling large-scale systems. The proposed MFD has a maximum force capacity of 200 kN (45 kips), with a dynamic range of 10 (ratio of the maximum force over the minimum force). The design can be extended to 1350 kN (300 kips), which will be used in the simulations for comparison with an actual large-scale passive mitigation system. Fig. 4.15b) shows the dynamics of the MR damper based under the Bouc-Wen model representation. Since the MFD has a friction element in lieu of a Bouc-Wen element, the main difference in the dynamics of those devices is in their hysteresis. The MR damper hysteresis loop in the force-velocity plot is typically larger.

As specified above, the MFD is at its conceptual phase. It is fundamental
CHAPTER 4. CONTROL DEVICES FOR LARGE-SCALE STRUCTURES

Figure 4.15: Schematic representation of the dynamics of a) the MFD; and b) the MR damper.

to utilize a model that accurately captures its dynamics. Several static and dynamic models have been developed to describe friction phenomena. Dynamic models are preferred over static models because of their higher precision and ease of simulation. Moreover, the hysteresis behavior of the friction element must be modeled in order to avoid unnecessary discontinuities in the force when velocity changes sign. The hysteresis phenomena will be discussed later. Among the existing dynamic models, such as the Dahl Model, the Bristle Model, the Reset Integrator Model, the models from Bliman and Sorine, and the LuGre model [149], the LuGre model has been selected due to its capacity to accurately simulate the Striebeck effect and rate dependance of the friction phenomenon. It has also been widely studied and is simple to simulate. The analytical representation of the LuGre model is written as:

\[
\dot{\sigma} = \dot{x} - \sigma_0 \frac{\left| \dot{x} \right|}{g(\dot{x})} z
\]

\[ F_{\text{friction}} = \sigma_0 z + \sigma_1 \dot{z} + f(\dot{x}) \]

where \( z \) is an evolutionary variable, \( F_{\text{friction}} \) is the reaction force from the friction element, \( f(\dot{x}) \) is the viscous friction and is commonly taken as \( f(\dot{x}) = \)
4.4. MODIFIED FRICTION DEVICE

\[ g(\dot{x}) = F_c + (F_s - F_c) e^{- (\dot{x}/\dot{x}_s)^\alpha} \]

where \( F_c \) is the Coulomb friction force, \( F_s \) is the magnitude of the Stribeck effect, \( \dot{x}_s \) and \( \alpha \) are constants. Note that at the steady-state (\( \dot{z} = 0 \)), the frictional force is uniquely described by \( F_c \) and the sign of the velocity: \( F_{\text{friction}} = F_c \text{sgn}(\dot{x}) \). Typical choices for \( \alpha \) are \( \alpha = 1 \) [192] and \( \alpha = 2 \) [149]. \( F_s \) is taken as proportional to \( F_c \), which allows the Stribeck effect to remain proportional to the applied voltage. The hysteresis phenomena is indirectly described in \( z \) by \( \sigma_0 \). The challenge in describing the hysteresis phenomenon for the MFD is in the limited information on the hysteresis found in large-scale friction devices. The hysteresis phenomena arises from slow processes, such as wear, accumulation of debris, and temperature variation, that cause a slow response to pressure changes [48]. Consequently, the hysteresis of a system is dependent on the friction material, load amplitude, and load frequency. Kim and Jeong [88] studied the hysteresis behavior of cast iron. The authors demonstrated that the hysteresis increases with applied stress and temperature, and decreases with heat. They also found that cast iron showed an hysteresis between 12.20 N·mm and 193.8 N·mm for a temperature ranging between 27.3°C and 34.7°C under high stresses applied at 25 Hz. Nevertheless, the hysteresis behavior of the MFD is expected to reach higher values because of the low frequency nature of the excitations. Thus, \( \sigma_0 \) is selected such that the hysteresis of the MFD stays in the range of the values described in [88] on low voltage (0-3 V).

To obtain values for \( \sigma_1, \sigma_2, F_s, \) and \( \dot{x}_s \), a model fit has been conducted on the experimental data of a 55 kN friction-type device. The fit is represented in Fig. 4.16. The resisting force \( F \) of the MFD can be written:

\[ F = F_{\text{friction}} + k_{\text{mfd}} x + c_{\text{mfd}} \dot{x}^\beta \]

where \( k_{\text{mfd}} \) and \( c_{\text{mfd}} \) are the stiffness and viscous coefficients of the MDF respectively, and \( \beta \) is a constant and taken as \( \beta = 1 \) for a linear viscous damper. While \( k_{\text{mfd}} \) can be designed based on the required stroke and dynamic range, \( c_{\text{mfd}} \) can be selected based on fail-safe requirements or for enhanced performance of the MFD. Those two values have been selected based on the performance requirements of the simulated structure. \( c_{\text{mfd}} \) is taken as
CHAPTER 4. CONTROL DEVICES FOR LARGE-SCALE STRUCTURES

Figure 4.16: Model fitting of a 55 kN friction-type device.

Table 4.3: MFD 200 kN parameter values.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\alpha$</td>
<td>2</td>
</tr>
<tr>
<td>$\beta$</td>
<td>1</td>
</tr>
<tr>
<td>$\sigma_0$</td>
<td>$5 \times 10^7$ kN/m</td>
</tr>
<tr>
<td>$\sigma_1$</td>
<td>$1 \times 10^5$ kN·s/m</td>
</tr>
<tr>
<td>$\sigma_2$</td>
<td>6.5 kN·s/m</td>
</tr>
<tr>
<td>$\dot{x}_s$</td>
<td>0.002 m/s</td>
</tr>
<tr>
<td>$F_s$</td>
<td>1.17 $F_c$</td>
</tr>
<tr>
<td>$F_{c_{\text{max}}}$</td>
<td>160 kN</td>
</tr>
<tr>
<td>$k_{\text{mfd}}$</td>
<td>$2 \times 10^4$ kN/m</td>
</tr>
<tr>
<td>$c_{\text{mfd}}$</td>
<td>$1.2 \times 10^4$ kN·s/m</td>
</tr>
</tbody>
</table>

12 MN·s/m, which is a tenth of the large-scale viscous dampers. The force-displacement plot and the force-velocity plot under an harmonic excitation of 0.5 Hz with an amplitude of 0.30 m for different levels of $F_c$ are shown in Fig. 4.17a) and Fig. 4.17b) respectively. Table 4.3 gives the parameter values used to model the MFD 200 kN dynamics. Note that in the case of the MFD 1350 kN, only $F_{c_{\text{max}}}$ changes, and takes the value $F_{c_{\text{max}}} = 1120$ kN. Fig. 4.18 illustrates the free body diagram of the MFD system. In an application, the drum would most likely be designed to roll on a flat surface.
4.4. MODIFIED FRICTION DEVICE

4.4.2 Friction Mechanism

Large capacity friction devices have been used for decades by the railroad industry. Fig. 4.19 shows a 50 kN-m (36 kips-ft) draft gear capacity at 2200 kN (500 kips) reaction force, which is designed to absorbed potential impacts of two adjacent cars. The challenge is to develop a device capable of large variable friction forces, while being mechanically reliable. The force variation must also be continuous in order to minimize accelerations in the controlled plant. The authors propose a variable friction mechanism based on existing mechanically reliable vehicle braking technologies: a duo-servo drum brake. The next subsection will derive the governing equations for duo-servo drum brakes, and will be followed by a description of the design of the braking mechanism.

Governing Equations for Duo-Servo Drum Brakes

The duo-servo drum brake is composed of two internal shoes anchored at a single pin, and attached with a rigid or floating link. A single hydraulic actuator exerts force on both shoes. Fig. 4.20a) illustrates the concept, and Fig. 4.20b) shows the force diagram for a negligible angle $\alpha$. For clarity of Fig. 4.20, the connection of the shoes to the pin is not shown. In Fig. 4.20b), $N$ is the normal force to the friction force $F$, $r$ is the radius, $W$ is the actuation force, $R_{\text{link}}$ is the force reaction from the link, $R_x$ and $R_y$ are the reactions...
from the pin in the $x$ and $y$ directions respectively, and subscripts 1 and 2 indicate the shoes. For this design, the floating link scheme is selected. That type of braking system has been shown to have a higher force amplification factor than most of other types of drum brakes, because of the self-energizing nature of the mechanism in both spinning directions [121].

The amplification factor of the actuation force $W$ to the tangential forces

---

Figure 4.18: Schematic of the braking mechanism in the MFD.

Figure 4.19: Mark 50 draft gear [39].
4.4. MODIFIED FRICTION DEVICE

Figure 4.20: Duo-servo drum brake: a) schematic; and b) force diagram.
CHAPTER 4. CONTROL DEVICES FOR LARGE-SCALE STRUCTURES

$F_i (i = 1, 2)$ is termed the force amplification factor $C$. The total frictional force is written $F_1 + F_2 = F_c = CW$, where $F_c$ is the coulomb force in (4.2). Specifically, using the notation for Fig. 4.20b and summing forces for the left shoe [121]:

\[
Wa + F_1r = R_{\text{link}}a \tag{4.4}
\]

and noting that for $\alpha$ negligible:

\[
R_{\text{link}} \approx \sqrt{F_1^2 + N_1^2} - W = \frac{F_1}{\mu} \sqrt{1 + \mu^2} - W \tag{4.5}
\]

where $\mu$ is the friction coefficient between the drum and the shoes, equation (4.4) becomes:

\[
W(a + b) = F_1 \left( \frac{a\sqrt{1 + \mu^2} - \mu r}{\mu} \right) \tag{4.6}
\]

where the amplification factor for the left shoe is given by:

\[
C_{\text{left}} = \frac{F_1}{W} = \frac{\mu(a + b)}{a\sqrt{1 + \mu^2} - \mu r} \tag{4.7}
\]

Similarly, for the right shoe, the summation of forces gives:

\[
R_{\text{link}}a + F_2r - Wb = R_xr \tag{4.8}
\]

where:

\[
R_x = N_2 - W - R_{\text{link}} \tag{4.9}
\]

such that (4.8) becomes:
4.4. MODIFIED FRICTION DEVICE

\[
R_{\text{link}}a + F_2r - Wb = (N_2 - W - R_{\text{link}})r \\
\left( \frac{F_1}{\mu} \sqrt{1 + \mu^2} - W \right)(a + r) - W(b - r) = F_2 \frac{r(1 - \mu)}{\mu} \\
\left( \frac{F_1}{\mu} \sqrt{1 + \mu^2} \right)(a + r) - W(a + b) = F_2 \frac{r(1 - \mu)}{\mu} \\
F_1 \frac{\sqrt{1 + \mu^2} a + r}{1 - \mu} - W \frac{(a + b)}{r} \frac{\mu}{1 - \mu} = F_2 \\
F_1 \frac{\sqrt{1 + \mu^2} a + r}{r} - W \frac{(a + b)}{r} \frac{\mu}{1 - \mu} = \frac{F_2}{W} \tag{4.10}
\]

An expression for the amplification factor of the right shoe can be written:

\[
C_{\text{right}} = C_{\text{left}} \left( \frac{a + r}{r} \sqrt{1 + \mu^2} \frac{1}{1 - \mu} \right) - \frac{(a + b)}{r} \frac{\mu}{1 - \mu} \tag{4.11}
\]

which gives an expression for the total amplification factor \( C = C_{\text{left}} + C_{\text{right}} \):

\[
C = \frac{\mu(a + b)}{a \sqrt{1 + \mu^2} - \mu r} \left[ 1 + \left( \frac{a + r}{r} \sqrt{1 + \mu^2} \frac{1}{1 - \mu} \right) \right] - \frac{a + b}{r} \frac{\mu}{1 - \mu} \tag{4.12}
\]

Fig. 4.21 shows the pressure distribution for the duo-servo brake drum. It is assumed that the distribution follows a triangular shape:

\[
p(\phi) = \frac{\phi p_{\text{max}}}{(\theta_1 + \theta_2)} \text{ for } \phi \leq \theta_1 \tag{4.13}
\]

\[
p(\phi) = \frac{(\phi - \theta_3)p_{\text{max}}}{(\theta_1 + \theta_2)} \text{ for } \theta_1 + \theta_3 \leq \phi \leq \theta_1 + \theta_2 + \theta_3
\]

where \( p_{\text{max}} \) is the maximum pressure and can be written as a function of the total pressure \( p_{\text{tot}} \):

\[
p_{\text{max}} = 2 \frac{p_{\text{tot}}}{\theta_1 + \theta_2} \tag{4.14}
\]
Recognizing that, in the case of civil structures, the braking pressure will be required for both rotating directions, it is useful to write (4.13) in term of a uniformly distributed average pressure $p_{\text{avg}}$:

$$\quad p_{\text{avg}} = \frac{p_{\text{max}}}{2} \tag{4.15}$$

The frictional torque $\tau_f$ can be computed using the moment of the tangential frictional force $F_{\text{friction}}$ about the center of the drum [49]:

$$d\tau_f = r \, dF \tag{4.16}$$

with:

$$dF = \mu b r d\phi$$

where $b$ is the shoe width. Integrating over the shoes leads to:

$$\tau_f = \int_{\theta_2}^{\theta_1} \mu b_r r^2 \frac{\phi p_{\text{max}}}{(\theta_1 + \theta_2)} \, d\phi + \int_{\theta_1 + \theta_3}^{\theta_1 + \theta_2 + \theta_3} \mu b_r r^2 \frac{(\phi - \theta_3) p_{\text{max}}}{(\theta_1 + \theta_2)} \, d\phi$$

$$\tau_f = \int_{\theta_2}^{\theta_1} \mu b_r r^2 p_{\text{max}} \, d\phi$$

$$\tau_f = \frac{(\theta_1 + \theta_2)}{2} \mu b_r r^2 p_{\text{max}} \tag{4.17}$$
The work done by the brake $U_f$ is defined by:

$$dU_f = \tau_f \, d\omega = \frac{\tau_f}{r} \, dx$$  \hspace{1cm} (4.18)$$

and integrating (4.18) leads to:

$$U_f = \frac{\tau_f}{r} x$$

$$U_f = F_{\text{friction}} x$$  \hspace{1cm} (4.19)$$

where $x$ is the damper displacement, and $\omega$ is the angular velocity. For an average velocity, the frictional power $P_f$ (in kcal/sec) is given by:

$$P_f = 238.8 \frac{\tau_f \dot{x}}{r}$$  \hspace{1cm} (4.20)$$

where 238.8 is a conversion constant for $\tau_f$ in N·m and $\dot{x}/r$ in s$^{-1}$. The energy absorption of the adjacent material to the braking shoes over a short period of time is related to the friction work and leads to the following relationship for temperature increase [49]:

$$\Delta T = \frac{1}{4187} \frac{U_f}{w_m c}$$  \hspace{1cm} (4.21)$$

where $1/4187$ is a conversion constant for $T$ in °C, $U_f$ in N·m, $w_m$ the mass of the material absorbing the energy in kg, and $c$ the average specific heat of the material in kcal/kg·°C. The allowable energy absorption by the braking mechanism is dependent on the lining material, the coefficient of friction $\mu$, and the rate of energy absorption. A greater shoe pad area would allow a greater energy dissipation, thus decreasing brake wear and fading. In the case of civil structure, the brake application is assumed to be of high intensity over infrequent short periods of time. For such, literature [49] suggests high allowable design values for energy dissipation.

**Design of the Braking Mechanism**

Asbestos was one of the most commonly used brake lining material due to its good mechanical properties and low cost availability, but health concerns
have led to its replacement by asbestos-free materials, such as semi-metallic, organic, and ceramic fibers friction materials. Han and Yin [61] studied the performance of added ceramic fibers to 15% weight steel fiber lining. Their study showed that the coefficient of friction remained above $\mu = 0.46$ for temperatures ranging from 100°C to 350°C for a 10% weight added ceramic fiber, thus offering a good resistance to fade. The wear rate of that material is approximately $1.6 \times 10^{-7}$ cm$^3$·(N·m)$^{-1}$.

Thus, cast iron using a steel fiber lining with added ceramic fibers is used for the drum and shoes. The design values are: $\mu = 0.46$, $c = 0.13$ kcal/kg·°C, and $w_m = 7500$ kg/m$^3$. The allowable maximum pressure is taken as $p_{\text{max,all}} = 130$ MPa.

The maximum required frictional force is $F_{\text{friction}} = 180$ kN for a 200 kN MFD, and $F_{\text{friction}} = 1200$ kN for a 1350 kN MFD. Selecting a shoe width $b_w = 0.1$ m and thickness $t_w = 0.025$ m for both shoes covering $0.65\pi$ each, and a drum radius of $r = 0.2$ m, the maximum pressure at any time is $p_{\text{max}} = 15.1$ MPa for the 200 kN MFD, and $p_{\text{max}} = 118$ MPa for the 1350 kN MFD. Two 2 kN linear hydraulic actuator operating on 12 volts are installed at 0.086 m up from the center of the drum, and shoes terminate at 0.15 m down from the center of the drum, giving a force amplification factor (4.12) of 58.5, which translates into a theoretical frictional capacity of 234 kN. For the 1350 kN MFD, the actuation force demand would be of 20 kN, which would be equivalent to 10 times the number of linear actuator needed in the 200 kN MFD case. A design trade-off would be to use bigger power sources for larger capacity actuators, at the expense of the independence on an external power source.

### 4.4.3 Brake Actuator Control

Several controllers have been proposed for control of variable friction devices, such as the bang-bang controller presented by Wu & Soong [208], along with its modifications with a SMC [26], an adaptive rule [108], a fuzzy rule [105], and a genetic algorithm [104]. Those controllers are designed to include the variable friction mechanism in the feedback rule. In contrast, the brake controller presented in this subsection is an internal controller to facilitate the incorporation of the device in any closed-loop system. It is decoupled from the controller that computes the required force. The device is designed to receive a required force and the internal controller computes a voltage based on that force. In the simulations, an LQR controller is used to feed the
required force to the brake controller.

A response delay of the linear actuator used in the braking mechanism is simulated by inducing a delay in the voltage response. The coulomb friction $F_c$ in (4.2) is written as:

$$F_c = F_{c,0} \cdot v_{\text{act}}$$

$$\dot{v}_{\text{act}} = -\eta(v_{\text{act}} - v_{\text{req}})$$

where $F_{c,0}$ is the nominal Coulomb friction and has a linear dependance on the actual voltage input $v_{\text{act}}$, $\eta$ is a positive constant representing the voltage delay, and $v_{\text{req}}$ is the required voltage for a desired force $F_{\text{req}}$. Here, the delay coefficient is taken as $\eta = 200$ to have a comparable dynamics with the 1000 N MR damper described in [46].

Two control rules are designed depending on the damper velocity state. In the region neighboring the hysteresis, the required voltage is applied following a saturation rule, where the voltage is maximum if the required force $F_{\text{req}}$ is higher than the actual force $F_{\text{act}}$ outputted by the damper, in absolute values, and of the same velocity sign. It is set to zero otherwise:

$$v_{\text{req}} = v_{\text{max}} \text{ if } |F_{\text{req}}| > |F_{\text{act}}| \text{ and } \text{sign}(F_{\text{req}}) = \text{sign}(\dot{x})$$

$$= 0 \text{ otherwise}$$

where $v_{\text{max}}$ is the maximum applicable voltage. This control rule is selected because of its simplicity in the region where the friction dynamics is complex to invert. The second control rule, outside the hysteresis region, is designed using a sliding controller. To select the required voltage $v$, consider the following Lyapunov function specialized for a scalar control force [170]:

$$V = \frac{1}{2}s^2$$

where $s$ is the sliding surface $s = F_{\text{act}} - F_{\text{req}}$. Taking the time derivative of (4.24), using (4.1), (4.2), (4.3) and (4.22), and recognizing that the system is at steady state ($g(\dot{x}) = F_c$ and $\dot{x} \neq 0$):
CHAPTER 4. CONTROL DEVICES FOR LARGE-SCALE STRUCTURES

\[ \dot{V} = s \left[ \tilde{F}_{\text{act}} - \dot{F}_{\text{req}} \right] \]

\[ = s \left[ \dot{F}_{\text{friction}} + k_{\text{mfd}} \ddot{x} + \beta c_{\text{mfd}} \dot{x}^{\beta-1} \ddot{x} - \dot{F}_{\text{req}} \right] \]

\[ = s \left[ \dot{F}_{c} \cdot \text{sgn}(\dot{x}) + \sigma_2 \ddot{x} + k_{\text{mfd}} \dddot{x} + \beta c_{\text{mfd}} \dot{x}^{\beta-1} \ddot{x} - \dot{F}_{\text{req}} \right] \]

\[ = s \left[ -F_{c,0} v_{\text{act}} \cdot \text{sgn}(\dot{x}) + F_{c,0} v_{\text{act}} \delta(\dot{x}) + \sigma_2 \ddot{x} + k_{\text{mfd}} \dddot{x} + \beta c_{\text{mfd}} \dot{x}^{\beta-1} \ddot{x} - \dot{F}_{\text{req}} \right] \]

\[ = -\xi s^2 \]

(4.25)

where \( \xi \) is a positive constant, the control voltage is selected to be:

\[ v_{\text{req}} = v_{\text{act}} + \frac{-\sigma_2 \ddot{x} - k_{\text{mfd}} \dot{x} - \beta c_{\text{mfd}} \dot{x}^{\beta-1} \ddot{x} + \dot{F}_{\text{req}} - \xi s}{\eta F_{c,0}} \text{sgn}(\dot{x}) \]  

(4.26)

Note that \( \dot{F}_{\text{req}} \) cannot be directly measured, but can be approximated as \( \dot{F}_{\text{req}} \approx (F_{\text{req}}(t) - F_{\text{req}}(t-1)) / \Delta t \). The term \( \xi \) can incorporate system uncertainties or unmeasurable states.

Fig. 4.22 shows a 200 kN frictional brake controlled using (4.26) and (4.23) for a required damping force of 100 kN. The saturation control rule within the hysteresis region is clearly shown.

4.5 Conclusion

In this chapter, we have reviewed different semi-active, active, and hybrid systems for application to control of large-scale structures. It has been shown in the literature that MR dampers are promising devices for vibration mitigation. However, their application is still in its infancy. We have suggested reasons impeding this acceptability, which are issues mainly related to their mechanical robustness.

As a consequence, we have introduced a new semi-active device for control of large-scale structures based on the MR damper dynamics: the MFD. The device has the advantage of using existing reliable technologies, which makes
4.5. CONCLUSION

Figure 4.22: MFD behavior for a 100 kN required damping force under an harmonic excitation of 7.62 mm at 0.5 Hz: a) force-velocity; and b) voltage-velocity.

...it an excellent candidate for implementation. It is capable of a damping force in the order of $10^5$ N on a 12-volts battery, which is at least an order of magnitude greater that what we have surveyed in the literature. The device will be simulated in the next chapter.
Simulations on Existing Structure
5.1 Introduction

We have, so far, introduced a novel controller, the SOI-WNN, as well as a unique semi-active damping device, the MFD, in order to create a feasible, fully integrated closed-loop control system, for large-scale uncertain systems. In this section, we integrate the SOI-WNN and the MFD, and simulate the new control strategy as an hypothetical replacement to the existing passive viscous damping system of an existing structure located in Boston, MA. Beforehand, we will discuss the potential of the MFD alone, and assess the
sensitivity of the SOI-WNN controller to its non-adaptive parameters.

In what follows, Section 5.2 describes in detail the existing structure used for the simulation. Section 5.3 introduces the simulations by studying the performance of the proposed MFD itself as a potential mitigation device. Section 5.4 conversely focuses on the SOI-WNN itself, and assesses the sensitivity of the controller with respect to its non-adaptive parameters. This section is essential to demonstrate robustness of the controller. Section 5.5 begins the simulations of the integrated control system by subjecting the structure to a wind excitation. Section 5.6 continues the simulations by subjecting the structure to 30 different earthquake excitations. Section 5.7 quickly investigates the performance of the controller joined to an LQR scheme. Section 5.8 concludes the chapter.

5.2 Simulated Structure

A 39-story office tower located in downtown Boston, Massachusetts, is simulated for comparing and assessing the performance of the proposed semi-active device. The building was built in the 1990’s with fluid dampers in order to mitigate excessive acceleration levels produced by the proximity of an existing 52-story tower. The cost of the passive system was less than a million dollars \cite{126}. Dampers are installed every other story from the 5th floor up to the 34th floor. The structural system along with the dampers location is shown in Fig. 5.1.

The viscous dampers in the X-direction have a capacity of 1350 kN (300 kips) with a damping coefficient of 52550 kN·s/m (300 kips·s/in) below the 26th floor, and a capacity of 900 kN (200 kips) with a damping coefficient of 35000 kN·s/m (200 kips·s/in) from the 26th floor and above. The viscous dampers in the Y-direction have a capacity of 90 kN (20 kips) with a damping coefficient of 3500 kN·s/m (20 kips·s/in) below the 26th floor, and a capacity of 45 kN (10 kips) with a damping coefficient of 1750 kN·s/m (10 kips·s/in) from the 26th floor and above. Moreover, the viscous dampers in the Y-direction are installed using toggle braces \cite{186} that amplify inter-story motion, and is illustrated in Fig. 5.2. A description of the actual damping strategy contained in the building can be found in \cite{126}, and details about the computer model are given in \cite{151}. For completeness, structural properties are given in Table 5.1, along with its fundamental periods in Table 5.2. Table 5.2 also compares the periods with values reported in \cite{126} from a wind tunnel testing. The first
Figure 5.1: Elevation view of the simulated structure: a) X-direction; and b) Y-direction.
5.2. SIMULATED STRUCTURE

Figure 5.2: Toggle brace damper system [40].

Period in both directions and twist match the experimental data, while the second period in both directions and twist has a discrepancy of approximately 10%. Table 5.3 summarizes the configuration of the viscous dampers.

Table 5.2: Fundamental periods and comparison with values reported in [126] from a wind tunnel testing.

<table>
<thead>
<tr>
<th>mode shape</th>
<th>direction</th>
<th>model period (s)</th>
<th>reported in [126] period (s)</th>
<th>difference (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>X</td>
<td>5.28</td>
<td>5.26</td>
<td>+0.38</td>
</tr>
<tr>
<td>2</td>
<td>Y</td>
<td>5.00</td>
<td>5.00</td>
<td>0.00</td>
</tr>
<tr>
<td>3</td>
<td>$\theta$</td>
<td>3.63</td>
<td>3.65</td>
<td>-0.55</td>
</tr>
<tr>
<td>4</td>
<td>X</td>
<td>2.16</td>
<td>1.92</td>
<td>-12.5</td>
</tr>
<tr>
<td>5</td>
<td>Y</td>
<td>2.07</td>
<td>1.82</td>
<td>-13.7</td>
</tr>
<tr>
<td>6</td>
<td>$\theta$</td>
<td>2.01</td>
<td>1.71</td>
<td>-17.5</td>
</tr>
</tbody>
</table>
CHAPTER 5. SIMULATIONS ON EXISTING STRUCTURE

Table 5.1: Dynamic properties. $K$ is the stiffness, $C$ is the damping, $M$ is the mass, subscripts $X$ and $Y$ represent the X and Y directions, and subscript $\theta$ represents rotational.

![Table 5.1: Dynamic properties](image)
Table 5.3: Configuration of viscous dampers

<table>
<thead>
<tr>
<th></th>
<th>capacity (kN)</th>
<th>number of dampers</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>X-direction</td>
<td>Y-direction</td>
</tr>
<tr>
<td>below 26\textsuperscript{th} floor</td>
<td>1350</td>
<td>90</td>
</tr>
<tr>
<td>above 26\textsuperscript{th} floor</td>
<td>900</td>
<td>45</td>
</tr>
</tbody>
</table>

5.2.1 Dynamic Loads

The performance of the proposed integrated control scheme will be assessed throughout the chapter using different dynamic loads to simulate the exposition to moderate winds and to earthquakes.

Wind Load

For the wind simulation, a wind load has been generated and scaled to match the acceleration of the 37\textsuperscript{th} floor provided in [126]. As aforementioned, some problematic vibration responses have been detected during a wind tunnel test. Despite that we were capable of obtaining some key data to reproduce a model of the structure, we were not able to obtain enough information to be capable of reconstructing the wind load itself. From this point, we had to generate a wind excitation that would be realistic for Boston, MA, and also try to reproduce the roof acceleration response. To do so, we were able to find wind tunnel testing data of another existing structure located in Boston. Despite that the building was smaller, it had a similar surrounding. Thus, we took the data from the wind tunnel test, extrapolated for our structure of interest, and scaled the excitation to match the data from the roof acceleration time history. Fig. 5.3 shows our generated wind load on the roof and the first floor for both directions. Note that the section of the acceleration time series used (200 sec) is such that the maximum acceleration response occurs around the end of the excitation.

Earthquake Loads

A set of 30 earthquakes has been used for the simulation. The earthquakes are summarized in Table 5.4. Data have been obtained via the USGS database [193]. They consist of excitations of different magnitude and epicentral distances. Their unscaled time series are shown in Appendix A in Figs. A.1-
CHAPTER 5. SIMULATIONS ON EXISTING STRUCTURE

Figure 5.3: Wind load used for the simulation. a) X-direction; and b) Y-direction.

A.30. For the simulations, each earthquake was scaled at 0.12 g to match the Massachusetts Code.

Among the 30 earthquake, we note the Imperial Valley (Imperial Valley) 1940 earthquake. It will be used for a single earthquake simulation for the first part of the simulations (MFD only), and later revisited with our algorithm. We have taken this earthquake because of its numerous usages for simulations in the field. It has an impulsive start, as well as a surge after 25 seconds. Its dynamics is somewhat ideal to test the capability of the controller to learn, adapt, and forget.

5.2.2 Performance Indices

Later in this chapter, we will simulate the integrated control scheme: the SOI-WNN for the structure equipped with MFDs. To assess the performance of the control system, we defined seven performance indices. They are summarized in Table 5.5. Indices $J_1$ and $J_2$ concern displacement mitigation, where $J_1$ measures mitigation of maximum inter-story displacement, and $J_2$ is similar but specialized at the device locations. Indices $J_3$ to $J_5$ are for acceleration mitigation, where $J_3$ is for the entire structure, $J_4$ is at the device locations, and $J_5$ is measuring the performance of acceleration mitigation at the 37th floor. This specialized index is useful to measure the performance of
Table 5.4: List of simulated earthquakes.

<table>
<thead>
<tr>
<th>Location</th>
<th>Year</th>
<th>Station</th>
<th>Angle (deg)</th>
<th>Dist. (km)</th>
<th>Mechanism</th>
<th>Mag. (RS)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Big Bear City, CA</td>
<td>2003</td>
<td>Morongo Valley</td>
<td>090</td>
<td>49.3</td>
<td>strike-slip</td>
<td>4.92</td>
</tr>
<tr>
<td>Chi-Chi, Taiwan</td>
<td>1999</td>
<td>CHY012</td>
<td>000</td>
<td>59.0</td>
<td>reverse-oblique</td>
<td>7.62</td>
</tr>
<tr>
<td>Coalinga, CA</td>
<td>1983</td>
<td>Parkfield - Fault Zone 10</td>
<td>000</td>
<td>30.3</td>
<td>reverse</td>
<td>6.36</td>
</tr>
<tr>
<td>Coyote Lake, CA</td>
<td>1979</td>
<td>Gilroy Array #1</td>
<td>230</td>
<td>10.2</td>
<td>strike-slip</td>
<td>5.74</td>
</tr>
<tr>
<td>Denali, Alaska</td>
<td>2002</td>
<td>Anchorage - K2-03</td>
<td>090</td>
<td>263.6</td>
<td>strike-slip</td>
<td>7.90</td>
</tr>
<tr>
<td>Dinar, Turkey</td>
<td>1995</td>
<td>Dinar</td>
<td>090</td>
<td>0.0</td>
<td>normal</td>
<td>6.4</td>
</tr>
<tr>
<td>Duzce, Turkey</td>
<td>1999</td>
<td>Lamont 531</td>
<td>090</td>
<td>8.0</td>
<td>strike-slip</td>
<td>7.14</td>
</tr>
<tr>
<td>Erzincan, Turkey</td>
<td>1992</td>
<td>Erzincan</td>
<td>090</td>
<td>0.0</td>
<td>strike-slip</td>
<td>6.69</td>
</tr>
<tr>
<td>Friuli, Italy</td>
<td>1976</td>
<td>Barcis</td>
<td>000</td>
<td>49.1</td>
<td>reverse</td>
<td>6.5</td>
</tr>
<tr>
<td>Gilroy, CA</td>
<td>2002</td>
<td>San Fran. - Fire Stn. #17</td>
<td>050</td>
<td>108.1</td>
<td>strike-slip</td>
<td>4.90</td>
</tr>
<tr>
<td>Imperial Valley, CA</td>
<td>1940</td>
<td>El Centro Array #9</td>
<td>180</td>
<td>13.0</td>
<td>strike-slip</td>
<td>7.0</td>
</tr>
<tr>
<td>Irpinia, Italy</td>
<td>1980</td>
<td>Brienza</td>
<td>000</td>
<td>22.5</td>
<td>normal</td>
<td>6.90</td>
</tr>
<tr>
<td>Kern County, CA</td>
<td>1952</td>
<td>Taft Lincoln School</td>
<td>111</td>
<td>56.0</td>
<td>reverse</td>
<td>7.36</td>
</tr>
<tr>
<td>Kobe, Japan</td>
<td>1995</td>
<td>Nishi-Akashi</td>
<td>090</td>
<td>7.1</td>
<td>strike-slip</td>
<td>6.9</td>
</tr>
<tr>
<td>Kocaeli, Turkey</td>
<td>1999</td>
<td>Ambarlı</td>
<td>000</td>
<td>68.1</td>
<td>strike-slip</td>
<td>7.51</td>
</tr>
<tr>
<td>Loma Prieta, CA</td>
<td>1989</td>
<td>Oakland Title &amp; Trust</td>
<td>170</td>
<td>72.1</td>
<td>reverse-oblique</td>
<td>6.93</td>
</tr>
<tr>
<td>Mammoth Lakes, CA</td>
<td>1980</td>
<td>Long Valley Dam</td>
<td>000</td>
<td>14.3</td>
<td>strike-slip</td>
<td>5.69</td>
</tr>
<tr>
<td>Manjil, Iran</td>
<td>1990</td>
<td>Qazvin</td>
<td>066</td>
<td>050</td>
<td>strike-slip</td>
<td>7.37</td>
</tr>
<tr>
<td>Michoacan, Mexico</td>
<td>1985</td>
<td>Station 1</td>
<td>180</td>
<td>250</td>
<td>reverse</td>
<td>8.1</td>
</tr>
<tr>
<td>Nahanni, Canada</td>
<td>1985</td>
<td>Site 2</td>
<td>240</td>
<td>0.0</td>
<td>reverse</td>
<td>6.76</td>
</tr>
<tr>
<td>New Zealand</td>
<td>1987</td>
<td>Maraemui Primary School</td>
<td>040</td>
<td>68.7</td>
<td>normal</td>
<td>6.6</td>
</tr>
<tr>
<td>Norcia, Italy</td>
<td>1979</td>
<td>Bevagna</td>
<td>090</td>
<td>31.4</td>
<td>normal</td>
<td>5.90</td>
</tr>
<tr>
<td>Northridge, CA</td>
<td>1994</td>
<td>Santa Monica City Hall</td>
<td>090</td>
<td>17.3</td>
<td>reverse</td>
<td>6.69</td>
</tr>
<tr>
<td>Parkfield, CA</td>
<td>1966</td>
<td>Cholame #5</td>
<td>085</td>
<td>9.6</td>
<td>strike-slip</td>
<td>6.19</td>
</tr>
<tr>
<td>San Fernando, CA</td>
<td>1971</td>
<td>Pacoima Dam</td>
<td>164</td>
<td>0.0</td>
<td>reverse</td>
<td>6.61</td>
</tr>
<tr>
<td>San Francisco, CA</td>
<td>1957</td>
<td>Golden Gate Park</td>
<td>010</td>
<td>9.6</td>
<td>reverse</td>
<td>5.28</td>
</tr>
<tr>
<td>San Salvador, El Salv.</td>
<td>1986</td>
<td>National Geografical Inst</td>
<td>180</td>
<td>3.7</td>
<td>strike-slip</td>
<td>5.80</td>
</tr>
<tr>
<td>Spitak, Armenia</td>
<td>1988</td>
<td>Gukasian</td>
<td>000</td>
<td>24.0</td>
<td>reverse-oblique</td>
<td>6.77</td>
</tr>
<tr>
<td>Tabas, Iran</td>
<td>1978</td>
<td>Tabas</td>
<td>000</td>
<td>1.8</td>
<td>reverse</td>
<td>7.35</td>
</tr>
<tr>
<td>Victoria, Mexico</td>
<td>1980</td>
<td>Cerro Prieto</td>
<td>045</td>
<td>13.8</td>
<td>strike-slip</td>
<td>6.33</td>
</tr>
</tbody>
</table>

1: estimated and classified as far-field

the control system for mitigation of wind vibrations, because the 37th floor is the highest occupied floor. Index $J_6$ concerns the base shear. Indices $J_7$ to $J_{10}$ are specific to the control devices. They measure the peak and average control forces, as well as the maximum average voltage and global average voltage of devices, respectively. Note that in Table 5.5, $\delta_{\text{max}}$ denotes the maximum interstorey displacement for the uncontrolled case, $\ddot{x}_{\text{unc,max}}$ and $\dddot{x}_{\text{unc,max}}$ are the maximum uncontrolled accelerations of all floors and the 37th floor respectively, $V_{\text{base,max}}$ is the maximum base shear of the uncontrolled case, $a$ is the number of devices, $v_b$ is the voltage bound ($v_b = 2 \cdot 12 \cdot v = 24 \cdot v$), and $\Delta x_{u,i}$ is the change in displacement.
CHAPTER 5. SIMULATIONS ON EXISTING STRUCTURE

Table 5.5: Summary of the performance indices.

<table>
<thead>
<tr>
<th>index</th>
<th>performance</th>
<th>measure</th>
</tr>
</thead>
<tbody>
<tr>
<td>$J_1$</td>
<td>maximum inter-story displacement at device locations</td>
<td>$\frac{\max_{i,t}</td>
</tr>
<tr>
<td>$J_2$</td>
<td>maximum inter-story displacement at device locations</td>
<td>$\frac{\max_{j,t}</td>
</tr>
<tr>
<td>$J_3$</td>
<td>maximum floor acceleration at device locations</td>
<td>$\frac{\max_{i,t}</td>
</tr>
<tr>
<td>$J_4$</td>
<td>maximum floor acceleration at device locations</td>
<td>$\frac{\max_{j,t}</td>
</tr>
<tr>
<td>$J_5$</td>
<td>peak 37$^{\text{th}}$ floor acceleration</td>
<td>$\frac{\max_{i,t}</td>
</tr>
<tr>
<td>$J_6$</td>
<td>maximum base shear</td>
<td>$\frac{\max_{i,t}</td>
</tr>
<tr>
<td>$J_7$</td>
<td>peak control force</td>
<td>$\frac{\max_{i,t}</td>
</tr>
<tr>
<td>$J_8$</td>
<td>average peak control force over all devices</td>
<td>$\frac{1}{\alpha} \sum_i \left{ \max_{i,t}</td>
</tr>
<tr>
<td>$J_9$</td>
<td>maximum average voltage</td>
<td>$\frac{1}{v_b} \max_i \left{ \frac{1}{T} \int_0^T v_i , dt \right}$</td>
</tr>
<tr>
<td>$J_{10}$</td>
<td>average voltage over all devices</td>
<td>$\frac{1}{\alpha v_b} \sum_i \left{ \frac{1}{T} \int_0^T v_i , dt \right}$</td>
</tr>
</tbody>
</table>

### 5.3 MFD performance

In this section, we analyze the performance of the MFD device itself, as we should have done in Chapter 4, but have preferred to wait after introducing the simulated large-scale structure.

The MFD has been simulated as a replacement to the actual damping strategy for mitigation of accelerations caused by wind excitation. A first simulation is run using the MFD 200 kN at the actual viscous dampers location. A second simulation studies the performance of MFDs of equal capacity to the viscous dampers. A third simulation studies the possibility of a reduced number of dampers using the MFD 1350 kN in the X-direction to achieve a performance similar to the current viscous damping strategy. Lastly, despite that the current damping strategy is not designed for earthquake mitigation,
### 5.3. MFD PERFORMANCE

Table 5.6: Configuration of MFDs for each simulations.

<table>
<thead>
<tr>
<th>similation</th>
<th>excitation</th>
<th>location</th>
<th>capacity (kN)</th>
<th>number of dampers</th>
</tr>
</thead>
<tbody>
<tr>
<td>simulation 1</td>
<td>wind</td>
<td>below 26th floor</td>
<td>200</td>
<td>200</td>
</tr>
<tr>
<td></td>
<td></td>
<td>above 26th floor</td>
<td>200</td>
<td>200</td>
</tr>
<tr>
<td>simulation 2</td>
<td>wind</td>
<td>below 26th floor</td>
<td>1350</td>
<td>90</td>
</tr>
<tr>
<td></td>
<td></td>
<td>above 26th floor</td>
<td>900</td>
<td>45</td>
</tr>
<tr>
<td>simulation 3</td>
<td>wind</td>
<td>below 26th floor</td>
<td>1350</td>
<td>N/A</td>
</tr>
<tr>
<td></td>
<td></td>
<td>above 26th floor</td>
<td>1350</td>
<td>N/A</td>
</tr>
<tr>
<td>simulation 4</td>
<td>earthquake</td>
<td>below 26th floor</td>
<td>1350</td>
<td>90</td>
</tr>
<tr>
<td></td>
<td></td>
<td>above 26th floor</td>
<td>900</td>
<td>45</td>
</tr>
</tbody>
</table>

The performance of the MFD at inter-story displacement mitigation, as well as its impact on the floor accelerations, are studied under the ElCentro 1940 North-South component earthquake scaled to a maximum of 0.12 g. Table 5.6 summarizes the configuration of the MFDs for each simulation.

#### 5.3.1 Simulation 1

A first simulation is conducted on the structure using the MFD 200 kN. The control objective is acceleration mitigation for serviceability. The maximum acceleration profile is illustrated in Fig. 5.4 for both directions. The active control strategy refers to an ideal actuator saturating at the MFD capacity. The semi-active control case refers to an LQR controller computing the required force $F_{req}$ for the MFD. The passive-on case refers to a passive control using full voltage, and the passive-off case refers to passive control using no voltage. The passive-off case is essentially the fail-safe mechanism on its own (the spring and dashpot in parallel). The MFD without the fail-safe mechanism is also studies. Results show that the MFD 200 kN underperforms the 1350 kN viscous dampers in the X-direction, but is still capable of mitigating acceleration levels to the ranges of 50 mg. The good performance in the Y-direction is due to the larger device capacities, which is 15 times the 90 kN viscous capacity. For the control strategy, semi-active control gives similar performance compared to the passive-on case, in both directions. The fail-safe mechanism provides only a small mitigation. Its contribution is also found to be minimal when comparing results to the MFD without the fail-safe mechanisms. Certainly, the fail-safe mechanism could be designed with elements of higher capacity, depending on the design objectives.
Finally, the internal force actuation of the 10th MFD, as well as its voltage inputs in function of its velocity, are shown in Fig. 5.5 for the semi-active control case. The linear actuation force stays within the range of 4 kN, which is equivalent to two 2-kN linear actuators working on 12 V batteries.
5.3.2 Simulation 2

The second simulation compares MFDs of identical capacities to the viscous dampers currently installed in the building. Fig. 5.6 shows the maximum acceleration profile in both direction. The MFD strategy is clearly capable of outperforming the passive viscous strategy. In the X-direction, semi-active control reduces the maximum acceleration of the 37th floor by 59.2% compared to 46.7% for the viscous dampers. In the Y-direction, it is 27.4% versus 14.9% respectively.

5.3.3 Simulation 3

Inspired by the results from the second simulation, it is interesting to evaluate the number of MFDs that would be required to mitigate acceleration with similar performance to the viscous damping strategy. The X-direction is of interest because of the significant mitigation capacity of the MFDs demonstrated in the second simulation. Fig. 5.7 shows the maximum acceleration profile using an MFD every 6 floors starting at the 5th floor. Results show that semi-active control and the passive-on strategies are capable of similar performance, using 10 dampers (2 dampers per floor, each 5 floors) instead of 30 for the viscous case. The semi-active control scheme could result in

Figure 5.6: Maximum acceleration profile, simulation 2: a) X-direction; and b) Y-direction.
significant savings. Table 5.7 summarizes the maximum acceleration of the 37th floor under various control strategies. Remark: it was found that some devices under semi-active control do substantially more work than others, which signifies that a more optimal configuration could be established. This is out of the scope of this paper.

Interestingly, both semi-active and passive-on control schemes give similar performance. The passive-on case is in essence a passive damper where the brake actuator is replaced by a spring. Thus, no semi-active control is necessary for the passive-on case, which could decrease the cost of the MFD. However, as it will be shown in the next simulation, it does not hold
5.3. **MFD PERFORMANCE**

Table 5.8: Maximum increase in temperature (°C/50 sec).

<table>
<thead>
<tr>
<th>control strategy</th>
<th>X-direction</th>
<th>Y-direction</th>
</tr>
</thead>
<tbody>
<tr>
<td>simulation 1</td>
<td>semi-active control</td>
<td>12.8</td>
</tr>
<tr>
<td></td>
<td>passive-on</td>
<td>14.9</td>
</tr>
<tr>
<td>simulation 2</td>
<td>semi-active control</td>
<td>41.5</td>
</tr>
<tr>
<td></td>
<td>passive-on</td>
<td>73.2</td>
</tr>
<tr>
<td>simulation 3</td>
<td>semi-active control</td>
<td>60.6</td>
</tr>
<tr>
<td></td>
<td>passive-on</td>
<td>74.8</td>
</tr>
</tbody>
</table>

for earthquake mitigation. In addition, a passive MFD could not be used to mitigate small magnitude excitations, as a substantial motion would be required to set the drum in motion. Also, using full voltage increases the work done on the damper, thus its heat. Table 5.8 shows the increase in temperature of the MFDs for several control strategies. The MFD increases temperature over the 50 seconds excitation by several degrees. Consequently, a release of the braking mechanism could be necessary if the device is to be utilized over a longer period of time. Results are also consistent with the simulations. For instance, larger MFDs (simulations 2 and 3) produce more heat, and the utilization of a third of the devices (simulation 3) results in a large demand on the dampers, thus higher heat. The passive-on strategy does more work than the control cases, as one would expect.

Fig. 5.8 shows a comparison of hysteresis loops between the viscous damper and the MFD located between the 25th and the 26th floor. Fig. 5.8a compares results from the first simulation. The hysteresis loops are in similar ranges for both systems. A slight increase in the MFD capacity would hypothetically result in similar mitigation performance than the viscous strategy. Fig. 5.8b compares results from the third simulation. Clearly, using MFDs of larger capacities allows the hysteresis loops to immediately reach the full damping capacity, resulting in a more effective energy dissipation.

### 5.3.4 Simulation 4

A last simulation is conducted on the structure subjected to the ElCentro 1940 earthquake. The control objective is inter-story displacement mitigation to minimize structural damage. For this simulation, the configuration of the MFDs from the second simulation is studied. Table 5.9 summarizes the
maximum inter-story displacement. In the X-direction, semi-active control performs significantly better than the viscous damping case as well as the passive-on case. In the Y-direction, the passive-on case performs better. This is explained by the low controllability range of the MFD 90 kN (20 kips). Table 5.10 shows the maximum absolute acceleration of the structure under various control strategies, which includes the maximum acceleration of both the entire building $\ddot{x}_{1-39}, \ddot{y}_{1-39}$ and the maximum acceleration at the damper locations $\ddot{x}_{5-34}, \ddot{y}_{5-34}$. The control strategy does reduce the acceleration for the entire structure, but performs the same as the passive viscous strategy at the damper locations due to the added stiffness. The passive-on control strategy gives the best performance for acceleration mitigation.

Table 5.9: Maximum inter-story displacement.

<table>
<thead>
<tr>
<th>control strategy</th>
<th>X-direction</th>
<th></th>
<th>Y-direction</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>$</td>
<td>x</td>
<td>$ (mm)</td>
<td>reduction (%)</td>
</tr>
<tr>
<td>uncontrolled</td>
<td>27.9</td>
<td>36.0</td>
<td>36.0</td>
<td></td>
</tr>
<tr>
<td>viscous dampers</td>
<td>20.1</td>
<td>28.0</td>
<td>28.0</td>
<td>22.2</td>
</tr>
<tr>
<td>semi-active control</td>
<td>16.2</td>
<td>41.9</td>
<td>24.2</td>
<td>32.8</td>
</tr>
<tr>
<td>passive-on</td>
<td>19.6</td>
<td>29.8</td>
<td>23.1</td>
<td>35.8</td>
</tr>
</tbody>
</table>

Figure 5.8: Comparison of hysteresis loops between the viscous damper and the MFD located between the 25th and the 26th floor: a) results from simulation 1; and b) results from simulation 3.
5.4. SOI-WNN - Parameters Sensitivity

Table 5.10: Maximum absolute acceleration.

<table>
<thead>
<tr>
<th>control strategy</th>
<th>X-direction</th>
<th>Y-direction</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>$\ddot{x}_{1-39}$ (mg)</td>
<td>$\ddot{x}_{5-34}$ (mg)</td>
</tr>
<tr>
<td>uncontrolled</td>
<td>196</td>
<td>195</td>
</tr>
<tr>
<td>viscous dampers</td>
<td>186</td>
<td>171</td>
</tr>
<tr>
<td>semi-active control</td>
<td>180</td>
<td>172</td>
</tr>
<tr>
<td>passive-on</td>
<td>184</td>
<td>165</td>
</tr>
</tbody>
</table>

5.4 SOI-WNN - Parameters Sensitivity

We begin the parameter sensitivity analysis section by verifying the performance of the SOI-WNN controller to mitigate an harmonic excitation acting on the fundamental frequency. The harmonic excitation is an easy way to study the influence of the non-adaptive parameters, as we know that the upper bound on the mitigation is theoretically obtained by adding a maximum of stiffness and damping, thus a full voltage strategy. To stay consistent with the previous and upcoming simulations with the wind excitation, we will use the acceleration of the 37th floor as a measure of performance. Note that for simplicity, and because in this section we are mainly interested by studying the influence of some parameters, we will limit the simulations to a single direction (the X-direction) and to a single control strategy, which is the substitution of the viscous dampers by MFDs of same capacity (1350 kN).

Table 5.11 shows the principal non-adaptive parameters in the SOI-WNN that have to be user-defined. They are divided in network object categories, and this is how we intent to divide this section for the sensitivity analysis of parameters. The list is not exhaustive, but the non-adaptive parameters not shown have little consequences on the performance of the SOI-WNN, or can be easily determined. Those include initial parameters for new nodes, sigmoid functions, smoothing functions, among others. The next subsections will discuss our choices of parameters, and we will perform sensitivity analyzes when appropriate. Note that all analyzes were performed over 120 seconds at a sampling rate of 50 Hz. Also, unless specified otherwise, performance and network size plots were done with the 10th semi-active device, which is representative from the average performance.
### CHAPTER 5. SIMULATIONS ON EXISTING STRUCTURE

Table 5.11: List of non-adaptive parameters for 1350 kN MFDs.

<table>
<thead>
<tr>
<th>NN object</th>
<th>parameter class</th>
<th>parameter</th>
<th>value assigned</th>
</tr>
</thead>
<tbody>
<tr>
<td>inputs</td>
<td>lag ($\tau$)</td>
<td># bins (MI test)</td>
<td>20</td>
</tr>
<tr>
<td></td>
<td>dimension ($d$)</td>
<td>$R_{tot}$</td>
<td>15</td>
</tr>
<tr>
<td></td>
<td></td>
<td>$R_{A,tol}$</td>
<td>2</td>
</tr>
<tr>
<td></td>
<td>window size</td>
<td>$n$</td>
<td>100</td>
</tr>
<tr>
<td>hidden layer</td>
<td>min. nodal distance</td>
<td>$\eta$</td>
<td>0.025</td>
</tr>
<tr>
<td></td>
<td>min. error$^1$</td>
<td>$|P x|_{min}$</td>
<td>0.025</td>
</tr>
<tr>
<td></td>
<td>network resolution</td>
<td>$\lambda$</td>
<td>100$|P x|_{min}$</td>
</tr>
<tr>
<td></td>
<td>pruning</td>
<td>% weight</td>
<td>2%</td>
</tr>
<tr>
<td></td>
<td></td>
<td># flags</td>
<td>50</td>
</tr>
<tr>
<td>outputs</td>
<td>SMC</td>
<td>$C$</td>
<td>225 kN</td>
</tr>
<tr>
<td></td>
<td></td>
<td>$G_t$</td>
<td>1350 kN</td>
</tr>
<tr>
<td>training</td>
<td>BP error</td>
<td>$P$</td>
<td>parabolic</td>
</tr>
<tr>
<td></td>
<td>training weights$^2$</td>
<td>$\Gamma_\mu$</td>
<td>0.001</td>
</tr>
<tr>
<td></td>
<td></td>
<td>$\Gamma_\sigma$</td>
<td>0.1</td>
</tr>
<tr>
<td></td>
<td></td>
<td>$\Gamma_\gamma$</td>
<td>1000</td>
</tr>
</tbody>
</table>

$^1$ for inputs normalized to a magnitude of $10^{-1}$

$^2$ when non-adaptive

#### 5.4.1 Inputs

Selection of non-adaptive parameters for the inputs is directly associated with the SOI algorithm. 

As we have seen in Chapter 3, the observation lag $\tau$ is selected using the mutual information (MI) test. The test is conducted using a classification of data in bins to determine probabilistically the information gained from changing the value of $\tau$. Thus, the number of subdivisions (bins) will have a positive impact on the accuracy of the test, but will negatively affect the computation time. We have used 20 bins as a good trade-off between accuracy and computation time, and left it fixed. No sensitivity analysis is performed for this parameter.

Regarding the false nearest neighbors (FNN) test, the non-adaptive parameters are limited to the thresholds on the number % number of false neighbors $R_{tot}$, and the maximum distance of neighbors $R_{A,tol}$. Because our dynamic system has forcing, thus numerous crossings in the phase-space as we have previously discussed, we expect to have many true neighbors that
will be detected as false neighbors. Thus, we kept $R_{tot}$ high, and fixed it at 15. The maximum distance has been kept to twice the average Euclidean distance between neighbors. Those values are arbitrary and have been shown to give good results for several simulations of different nature (functional tracking, control of 3 DOF systems, control of 39 DOF systems, etc.). No sensitivity analyzes are performed for those parameters.

The sensitivity of the window size $n$ was analyzed in Section 3.6.1, and as we have previously showed, a window size $n = 100$ gives good results and computing performance. we did not discussed parameter selection for the lag and embedding dimension tests.

### 5.4.2 Hidden Layer

The hidden layer non-adaptive parameters mostly define the SOI-WNN self-organizing mapping (SOM), which consists of adding and pruning nodes. The minimum nodal distance $\eta$ defines the minimum Euclidean distance for which a node most me added. The minimum error $\|Px\|_{\min}$ is the minimum error allowed for adding a new node. Their values provided in Table 5.11 are taken for inputs normalized to a magnitude of $10^{-1}$. The network resolution $\lambda$ defines the bandwidth of a newly added node. Here, it has been set as a linear function of $\|Px\|_{\min}$, with a constant of 100.

We first investigate the sensitivity of the SOI-WNN with respect to that constant. Fig. 5.9 shows the network size and mitigation performance under different constant values. We can observe two different plateaux of mitigation performance. It appears that a larger constant (smaller resolution) provides a better performance. Counter-intuitively, the network size increases with the increasing linear constant, which corresponds to a decreasing resolution. We thus fix the linear constant to 100, which corresponds to the value before the network size seems to significantly increase, and run another sensitivity analysis by modifying the minimum error. Fig. 5.10 shows the results. Once again, we see two performance plateaux, and notice a change in performance when the network size decreases. The result is now intuitive, as the network size decreases with the decreased resolution, as $\lambda$ is a linear function of the minimum error. A minimum error smaller than $10^{-1}$ gives a stable performance. We chose $\|Px\|_{\min} = 0.025$.

In addition, we analyze the sensitivity of the SOI-WNN with respect to both the minimum distance and minimum error. Fig. 5.11 shows the network size and mitigation results. Results confirm that the performance
CHAPTER 5. SIMULATIONS ON EXISTING STRUCTURE

Figure 5.9: Network size and mitigation sensitivity in function of the linear constant for $\lambda$.

Figure 5.10: Network size and mitigation sensitivity in function of the minimum error $\eta$, with $\lambda = 100\|Px\|_\text{min}$. 

198
and network size remain insensitive to the minimum error for values beneath $10^{-1}$. Furthermore, there is a strong negative correlation between the network size and the minimum distance, as we would expect, and with the maximum acceleration. However, the decrease in performance with the decreasing minimum distance could easily be caused by the increased network size, where the SOI-WNN becomes too dense to appropriately converge to a good control rule. This hypothesis will be tested in the sensitivity analysis of the pruning parameters. For the simulations, we have selected a minimum distance of $\eta = 0.025$. The values for the minimum distances and errors correspond to the middle point in Fig. 5.11.

We now investigate the sensitivity of the pruning parameters. Pruning of the hidden layer is conducted if the nodal weight is below a % threshold of the largest weight for a set number of consecutive events, which we call flags. Fig. 5.12 shows the sensitivity analysis of the pruning parameters. We see that the average network size considerably increases with the allowed number of flags, as one would expect, and only slightly decrease with the pruning weight threshold. Remarkably, the mitigation performance does not seem to be significantly influenced by the pruning parameters. Thus, the number of flags, just like the pruning threshold, allows the network to keep useful nodes for a longer period of time. Nevertheless, the pruning threshold does not seem to influence much the SOI-WNN. For the simulations, we have selected
a pruning threshold of 2%, and a number of flag of 50 in order to keep the network lean for an enhanced computation time.

5.4.3 Outputs

The outputs of the SOI-WNN are the required forces sent to the control devices. A required force consists of the neural output, plus a compensation from the sliding controller. That compensation is done in function of adaptation regions defined in Chapter 2, $C$ and $C_t$. The size of the adaptation region $C$ allows the controller to undergo full adaptation ($m_c = 0$) even in the presence of some force output error $\tilde{u}$, while the transition region $C_t$ is a buffer region with a smoothly varying adaptation weight.

For the simulation, we have allowed for $C$ an error of 8.33%\textsuperscript{1} $u_b$ in order to speed up the adaptation process. The transition region has been fixed to 50% $u_b$. We would like to remind the reader that this value must remind high to try satisfying (2.76) negative-definite.

Fig. 5.13 shows the mitigation performances for various values of $C$ and $C_t$. We see that a low value for the adaptation region $C$ gives a better performance. Actually, a value of 0 is the best option. Nevertheless, a minimum value is

\textsuperscript{1}The reader might wonder why we have arbitrarily selected this ratio. It arose from the use of imperial units where we let the region be $50/(300 \times 2)$ kips.

![Figure 5.12: Sensitivity of pruning parameters. a) Network size; and b) mitigation performance.](image-url)
prescribed to account for higher variations in external excitations, where our $C = 225kN$. The mitigation performance also increases with the increasing transition region.

Another interesting investigation is the mitigation performance in function of both non-adaptive parameters. Fig. 5.14 shows the 37th floor maximum acceleration in function of both $C$ and $C_t$. The influence of region $C$ increases with the decreased region $C_t$, which shows the importance of conserving a certain transition region. The performance seems to remain stable for a high $C_t$, regardless of the size of the adaptation region $C$. The value obtained at $C = 0$ in Fig. 5.13 seems to have been misrepresentative of the global behavior with respect to regions.

5.4.4 Training

Non-adaptive training parameters have potentially the largest sensitivity on the network performance. We start by studying the choice of the sliding surface $P$. Typically, $P$ is built with parabolically decreasing weights for increasing height, as one would expect increasing inter-story displacements and velocities with increasing height. That way, we would keep the error approximately of the same magnitude for all damping devices. In addition, as
specified in Chapter 2, \( P \) needs to be constructed with opposite values at the
damper locations in order to represent local interstorey measurements. Given
that designing \( P \) with such requirements is a trivial task, where we can easily
construct an empty matrix and add opposite and parabolically decreasing
values at the damper locations, the question is how much weight shall we put
on those, and would those weights be different for inter-story displacement
and velocity measurements. For the sensitivity analysis, we assumed that
\( P \) is built with values \( P_{i,j} \in [-1, 1] \) and is divided between a displacement
surface \( P_{\text{disp}} \) and velocity surface \( P_{\text{vel}} \):

\[
P = [P_{\text{disp}} | P_{\text{vel}}]
\]  

and we assign weights to each types of measurements such that (5.2) becomes:

\[
\Delta P = [\Delta_{\text{disp}} P_{\text{disp}} | \Delta_{\text{vel}} P_{\text{vel}}]
\]  

where \( \Delta \) is a scalar weight on each sub-matrix. Fig. 5.15 shows the average
network size and the mitigation performance in function of the weights on
the sliding surface. The network size does not change significantly with \( \Delta \),
conversely to the controller performance. It appears that a large \( \Delta_{\text{disp}} \) gives
great mitigation performance. Nevertheless, we need to remember that the \( P \)
matrix is equivalent to the control weight matrix \( Q \) for LQR controllers. Thus,
large weights will result in large control force required, very often unrealistic.
If we look at the evolution of nodal weights, we can see the potential negative
impact of high sliding surface weights. Fig. 5.16 shows the evolution of nodal

![Figure 5.14: Mitigation sensitivity in function of various region bounds.](image)
weights of both the 1st MFD and 10 MFD (left and right figures) for the large and normal weights \( \Delta \) (top and bottom figures). Clearly, the large weights (top figures) result in unrealistic nodal weights (the MFD capacity is 1350 kN). In addition, we can observe that the nodal weights of the 10 MFD are large and all negative for large sliding surface weights. That corresponds to a bang-bang type controller, where the device voltage is switched on and off depending on the sign of the device’s velocity. The smaller weights (bottom figures) has a symmetric evolution, and within or close to the device’s force capacity. Note that the weights do not converge because the excitation is not persistent\(^1\).

For our simulations, we have selected the smaller sliding surface weighting values in order to kept nodal weights within the MFD ranges.

Lastly, we need to study the adaptation parameters \( \Gamma_\mu, \Gamma_\sigma, \) and \( \Gamma_\gamma \). Note that the adaptation weight on the node weights \( \gamma \) has a significant impact on the sensitivity of the sliding surface \( P \). Thus, we let \( \Gamma_\gamma \) fixed with diagonal elements \( \Gamma_{\gamma,i} = 1000 \). Nevertheless, we are interested in the sensitivity of the SOI-WNN with respect to the adaptation weights of the nodal centers \( \mu \) and bandwidths \( \sigma \). Fig. 5.17 shows the results from the simulations for different values of \( \Gamma_\mu \) and \( \Gamma_\sigma \). From Fig. 5.17b, we notice that the mitigation

\(^1\)An excitation is said to be persistent if it is rich enough to allow convergence of parameters due to the uniqueness of the system identification solution. See Narendra and Annaswamy [138] for a formal definition.
performance increases with $\Gamma_\mu$ decreasing and $\Gamma_\sigma$ increasing. However, from Fig. 5.17, we observe the converse behavior for the network size, and the network size does increase significantly for $\Gamma_\sigma$ reaching $10^9$. This mean that a large adaptation rate on the bandwidth will result in a finer resolution. For the simulations, we have kept $\Gamma_\mu$ at $10^{-3}$, and $\Gamma_\mu$ at 0.1.

Figure 5.16: Evolution of the nodal weights for error weights on displacements and velocities being respectively: a) $10^2$ and $10^1$, MFD #1; b) $10^2$ and $10^1$, MFD #1; c) $10^1$ and $10^1$, MFD #1; and d) $10^1$ and $10^1$, MFD #10.
5.5. SOI-WNN - WIND EXCITATION

5.4.5 Global Performance

Using the non-adaptive parameters described above, we now show the performance of the SOI-WNN controller with respect to the best fixed input strategy, which was found by searching the space $\tau = [1, 20], d = [1, 4]$. The optimal result was obtained by using $\tau = 9$ and $d = 1$. Fig. 5.18 shows the time series response of the structure for various control strategies. The SOI-WNN performs remarkably better than the optimal fixed inputs strategy, and converges to a mitigation similar to the LQR strategy. The passive-on case is the optimal mitigation strategy. Fig. 5.19 illustrates the evolution of the input vector parameters over time for the 10th controller (typical).

As a last sensitivity analysis, we would like to study the performance of the SOI-WNN with respect to measurement errors and induced delays. Fig. 5.20 shows the maximum acceleration after $t = 120$ sec for two random simulations (random on the error). The results are in function of different control delays and measurement errors on both the acceleration and force output measurements. The delay consists of delaying the response of the control device, while the measurement errors consist of adding a noise. The noise has a Gaussian distribution. Both simulations give similar results. It appears that the controller performance gives better performance for a delay of 200 ms, with a degradation for large delays (2000 ms). That increased performance for an induced delay can be explained by the control delay actually matching the induced voltage delay in the MFD dynamics. In addition, the controller seems to be only slightly negatively sensitive to increased measurement errors. Note that for all simulations, we have assumed no measurement error for ease of comparison, and used a delay in the devices’ voltage.

5.5 SOI-WNN - Wind Excitation

We here revisit the first three simulations performed on the MFD subjected to wind-induced displacements. We will take the LQR controller optimized in the previous simulations as an upper bound target on performance, and will repeat results from the passive viscous and uncontrolled performances for convenience. The measured local states are as aforementioned: for the SOI-WNN, local controller assumes knowledge of the device displacement and velocity, which linearly corresponds to interstorey displacement and velocity,
5.5.1 Revisiting Simulation 1

The first simulation consists of analyzing the performance of 200 kN capacity MFDs replacing the existing viscous dampers. Fig. 5.21 shows the maximum acceleration profile of the top 10 floors in both directions. The performance of the SOI-WNN is undistinguishable with the fixed-input strategy. Moreover, both of those neurocontrol strategies slightly outperform the optimized fixed input case. The acceleration mitigation of the SOI-WNN is close to the LQR performance, as summarized in Table 5.18. Results agree in both directions.

5.5.2 Revisiting Simulation 2

Simulation 2 investigates the performance of the control strategy using the SOI-WNN along with MFDs of similar capacities than the existing viscous dampers. Fig. 5.22 shows the maximum acceleration profile in both directions. Results are very similar to simulation 1, where the performance of the SOI-WNN is close to the LQR one, and similar to the fixed input strategies.
5.5. SOI-WNN - WIND EXCITATION

Figure 5.17: Sensitivity of the adaptation weights. a) Network size; and b) mitigation performance.

Table 5.13: Performance indices for wind mitigation, simulation 1, X-direction.

<table>
<thead>
<tr>
<th>index</th>
<th>visc.</th>
<th>LQR</th>
<th>SOI</th>
<th>FS</th>
<th>FI</th>
<th>ON</th>
<th>OFF</th>
</tr>
</thead>
<tbody>
<tr>
<td>J1</td>
<td>0.747</td>
<td>0.794</td>
<td>0.794</td>
<td>0.799</td>
<td>0.820</td>
<td>0.759</td>
<td>0.979</td>
</tr>
<tr>
<td>J2</td>
<td>0.768</td>
<td>0.826</td>
<td>0.849</td>
<td>0.849</td>
<td>0.857</td>
<td>0.803</td>
<td>0.985</td>
</tr>
<tr>
<td>J3</td>
<td>0.646</td>
<td>0.731</td>
<td>0.782</td>
<td>0.782</td>
<td>0.806</td>
<td>0.690</td>
<td>0.975</td>
</tr>
<tr>
<td>J4</td>
<td>0.674</td>
<td>0.795</td>
<td>0.817</td>
<td>0.819</td>
<td>0.850</td>
<td>0.771</td>
<td>0.976</td>
</tr>
<tr>
<td>J5</td>
<td>0.644</td>
<td>0.754</td>
<td>0.792</td>
<td>0.791</td>
<td>0.807</td>
<td>0.710</td>
<td>0.976</td>
</tr>
<tr>
<td>J6</td>
<td>0.662</td>
<td>0.790</td>
<td>0.819</td>
<td>0.817</td>
<td>0.839</td>
<td>0.752</td>
<td>0.987</td>
</tr>
<tr>
<td>J7</td>
<td>0.997</td>
<td>0.997</td>
<td>0.936</td>
<td>0.942</td>
<td>0.936</td>
<td>1.066</td>
<td>0.217</td>
</tr>
<tr>
<td>J8</td>
<td>0.947</td>
<td>0.947</td>
<td>0.891</td>
<td>0.899</td>
<td>0.889</td>
<td>1.046</td>
<td>0.171</td>
</tr>
<tr>
<td>J9</td>
<td>0.000</td>
<td>0.717</td>
<td>0.585</td>
<td>0.644</td>
<td>0.570</td>
<td>1.000</td>
<td>0.000</td>
</tr>
<tr>
<td>J10</td>
<td>0.000</td>
<td>0.664</td>
<td>0.534</td>
<td>0.584</td>
<td>0.520</td>
<td>1.000</td>
<td>0.000</td>
</tr>
</tbody>
</table>

FS: full states
FI: fixed inputs
with a slight improvement. Table 5.18 summarized the 37th floor acceleration mitigation.

5.5.3 Revisiting Simulation 3

For this simulation, we cut the number of MFDs in the X-direction to a third of the original dampers. This significantly reduces the reachability of the control system. Fig. 5.23 shows the mitigation performance of the SOI-WNN. We once again come to the same observations as for the previous two simulations. Table 5.18 summarizes the 37th floor acceleration mitigation.

A general conclusion that we can draw from the wind simulation is that the performance of the SOI-WNN is constantly close to the LQR control strategy (which assumes full state and parametric knowledge), and similar to the fixed input strategies with a small improvement of acceleration mitigation.

5.6 SOI-WNN - Earthquake Excitations

5.6.1 Revisiting Simulation 4

We start the SOI-WNN earthquake mitigation performance study by revisiting simulation 4 that we have conducted in Section 5.3.4. Table 5.19 shows the
5.6. SOI-WNN - EARTHQUAKE EXCITAIONS

Figure 5.19: Evolution of the input vector for the 10th controller.

Table 5.14: Performance indices for wind mitigation, simulation 1, Y-direction.

<table>
<thead>
<tr>
<th>index</th>
<th>visc.</th>
<th>LQR</th>
<th>SOI</th>
<th>FS</th>
<th>FI</th>
<th>ON</th>
<th>OFF</th>
</tr>
</thead>
<tbody>
<tr>
<td>J1</td>
<td>0.625</td>
<td>0.526</td>
<td>0.518</td>
<td>0.522</td>
<td>0.520</td>
<td>0.569</td>
<td>0.689</td>
</tr>
<tr>
<td>J2</td>
<td>0.695</td>
<td>0.793</td>
<td>0.781</td>
<td>0.788</td>
<td>0.782</td>
<td>0.861</td>
<td>0.758</td>
</tr>
<tr>
<td>J3</td>
<td>0.661</td>
<td>0.690</td>
<td>0.648</td>
<td>0.660</td>
<td>0.660</td>
<td>0.710</td>
<td>0.664</td>
</tr>
<tr>
<td>J4</td>
<td>0.517</td>
<td>0.508</td>
<td>0.508</td>
<td>0.506</td>
<td>0.510</td>
<td>0.435</td>
<td>0.591</td>
</tr>
<tr>
<td>J5</td>
<td>0.543</td>
<td>0.508</td>
<td>0.499</td>
<td>0.500</td>
<td>0.501</td>
<td>0.484</td>
<td>0.602</td>
</tr>
<tr>
<td>J6</td>
<td>0.582</td>
<td>0.541</td>
<td>0.537</td>
<td>0.538</td>
<td>0.539</td>
<td>0.482</td>
<td>0.676</td>
</tr>
<tr>
<td>J7</td>
<td>0.997</td>
<td>0.991</td>
<td>0.894</td>
<td>0.900</td>
<td>0.923</td>
<td>1.279</td>
<td>0.471</td>
</tr>
<tr>
<td>J8</td>
<td>0.947</td>
<td>0.857</td>
<td>0.806</td>
<td>0.833</td>
<td>0.815</td>
<td>1.196</td>
<td>0.415</td>
</tr>
<tr>
<td>J9</td>
<td>0.000</td>
<td>0.570</td>
<td>0.503</td>
<td>0.531</td>
<td>0.515</td>
<td>1.000</td>
<td>0.000</td>
</tr>
<tr>
<td>J10</td>
<td>0.000</td>
<td>0.494</td>
<td>0.458</td>
<td>0.502</td>
<td>0.480</td>
<td>1.000</td>
<td>0.000</td>
</tr>
</tbody>
</table>

FS: full states
FI: fixed inputs
### Table 5.15: Performance indices for wind mitigation, simulation 2, X-direction.

<table>
<thead>
<tr>
<th>index</th>
<th>visc.</th>
<th>LQR</th>
<th>SOI</th>
<th>FS</th>
<th>FI</th>
<th>ON</th>
<th>OFF</th>
</tr>
</thead>
<tbody>
<tr>
<td>J1</td>
<td>0.747</td>
<td>0.567</td>
<td>0.566</td>
<td>0.607</td>
<td>0.613</td>
<td>0.629</td>
<td>0.882</td>
</tr>
<tr>
<td>J2</td>
<td>0.768</td>
<td>0.803</td>
<td>0.764</td>
<td>0.758</td>
<td>0.752</td>
<td>0.941</td>
<td>0.898</td>
</tr>
<tr>
<td>J3</td>
<td>0.646</td>
<td>0.493</td>
<td>0.451</td>
<td>0.501</td>
<td>0.516</td>
<td>0.598</td>
<td>0.663</td>
</tr>
<tr>
<td>J4</td>
<td>0.674</td>
<td>0.449</td>
<td>0.504</td>
<td>0.502</td>
<td>0.473</td>
<td>0.546</td>
<td>0.857</td>
</tr>
<tr>
<td>J5</td>
<td>0.644</td>
<td>0.457</td>
<td>0.438</td>
<td>0.469</td>
<td>0.470</td>
<td>0.516</td>
<td>0.855</td>
</tr>
<tr>
<td>J6</td>
<td>0.662</td>
<td>0.479</td>
<td>0.502</td>
<td>0.484</td>
<td>0.478</td>
<td>0.556</td>
<td>0.865</td>
</tr>
<tr>
<td>J7</td>
<td>0.829</td>
<td>0.829</td>
<td>0.887</td>
<td>0.968</td>
<td>0.962</td>
<td>1.060</td>
<td>0.178</td>
</tr>
<tr>
<td>J8</td>
<td>0.733</td>
<td>0.733</td>
<td>0.841</td>
<td>0.884</td>
<td>0.891</td>
<td>1.036</td>
<td>0.150</td>
</tr>
<tr>
<td>J9</td>
<td>0.000</td>
<td>0.501</td>
<td>0.537</td>
<td>0.539</td>
<td>0.558</td>
<td>1.000</td>
<td>0.000</td>
</tr>
<tr>
<td>J10</td>
<td>0.000</td>
<td>0.420</td>
<td>0.445</td>
<td>0.515</td>
<td>0.496</td>
<td>1.000</td>
<td>0.000</td>
</tr>
</tbody>
</table>

FS: full states
FI: fixed inputs

### Table 5.16: Performance indices for wind mitigation, simulation 2, Y-direction.

<table>
<thead>
<tr>
<th>index</th>
<th>visc.</th>
<th>LQR</th>
<th>SOI</th>
<th>FS</th>
<th>FI</th>
<th>ON</th>
<th>OFF</th>
</tr>
</thead>
<tbody>
<tr>
<td>J1</td>
<td>0.625</td>
<td>0.726</td>
<td>0.651</td>
<td>0.636</td>
<td>0.650</td>
<td>0.570</td>
<td>0.750</td>
</tr>
<tr>
<td>J2</td>
<td>0.695</td>
<td>0.726</td>
<td>0.760</td>
<td>0.762</td>
<td>0.760</td>
<td>0.754</td>
<td>0.750</td>
</tr>
<tr>
<td>J3</td>
<td>0.661</td>
<td>0.783</td>
<td>0.753</td>
<td>0.738</td>
<td>0.753</td>
<td>0.661</td>
<td>0.777</td>
</tr>
<tr>
<td>J4</td>
<td>0.517</td>
<td>0.572</td>
<td>0.561</td>
<td>0.555</td>
<td>0.560</td>
<td>0.533</td>
<td>0.583</td>
</tr>
<tr>
<td>J5</td>
<td>0.543</td>
<td>0.642</td>
<td>0.568</td>
<td>0.561</td>
<td>0.568</td>
<td>0.527</td>
<td>0.674</td>
</tr>
<tr>
<td>J6</td>
<td>0.582</td>
<td>0.717</td>
<td>0.628</td>
<td>0.613</td>
<td>0.627</td>
<td>0.551</td>
<td>0.744</td>
</tr>
<tr>
<td>J7</td>
<td>0.829</td>
<td>1.210</td>
<td>0.926</td>
<td>0.978</td>
<td>0.939</td>
<td>1.321</td>
<td>0.502</td>
</tr>
<tr>
<td>J8</td>
<td>0.733</td>
<td>1.143</td>
<td>0.877</td>
<td>0.917</td>
<td>0.878</td>
<td>1.259</td>
<td>0.440</td>
</tr>
<tr>
<td>J9</td>
<td>0.000</td>
<td>0.819</td>
<td>0.505</td>
<td>0.560</td>
<td>0.540</td>
<td>1.000</td>
<td>0.000</td>
</tr>
<tr>
<td>J10</td>
<td>0.000</td>
<td>0.772</td>
<td>0.485</td>
<td>0.538</td>
<td>0.486</td>
<td>1.000</td>
<td>0.000</td>
</tr>
</tbody>
</table>

FS: full states
FI: fixed inputs
### 5.6. SOI-WNN - EARTHQUAKE EXCITATIONS

Table 5.17: Performance indices for wind mitigation, simulation 3.

<table>
<thead>
<tr>
<th>index</th>
<th>visc.</th>
<th>LQR</th>
<th>SOI</th>
<th>FS</th>
<th>FI</th>
<th>ON</th>
<th>OFF</th>
</tr>
</thead>
<tbody>
<tr>
<td>J1</td>
<td>0.747</td>
<td>0.784</td>
<td>0.787</td>
<td>0.806</td>
<td>0.794</td>
<td>0.720</td>
<td>0.947</td>
</tr>
<tr>
<td>J2</td>
<td>0.721</td>
<td>0.688</td>
<td>0.703</td>
<td>0.726</td>
<td>0.719</td>
<td>0.700</td>
<td>0.902</td>
</tr>
<tr>
<td>J3</td>
<td>0.646</td>
<td>0.732</td>
<td>0.750</td>
<td>0.765</td>
<td>0.757</td>
<td>0.626</td>
<td>0.943</td>
</tr>
<tr>
<td>J4</td>
<td>0.587</td>
<td>0.577</td>
<td>0.612</td>
<td>0.634</td>
<td>0.665</td>
<td>0.660</td>
<td>0.808</td>
</tr>
<tr>
<td>J5</td>
<td>0.644</td>
<td>0.698</td>
<td>0.713</td>
<td>0.757</td>
<td>0.717</td>
<td>0.629</td>
<td>0.941</td>
</tr>
<tr>
<td>J6</td>
<td>0.662</td>
<td>0.639</td>
<td>0.702</td>
<td>0.721</td>
<td>0.722</td>
<td>0.596</td>
<td>0.961</td>
</tr>
<tr>
<td>J7</td>
<td>0.883</td>
<td>0.883</td>
<td>0.886</td>
<td>0.903</td>
<td>0.925</td>
<td>1.041</td>
<td>0.185</td>
</tr>
<tr>
<td>J8</td>
<td>0.859</td>
<td>0.859</td>
<td>0.856</td>
<td>0.870</td>
<td>0.888</td>
<td>1.020</td>
<td>0.161</td>
</tr>
<tr>
<td>J9</td>
<td>0.000</td>
<td>0.636</td>
<td>0.547</td>
<td>0.529</td>
<td>0.565</td>
<td>1.000</td>
<td>0.000</td>
</tr>
<tr>
<td>J10</td>
<td>0.000</td>
<td>0.603</td>
<td>0.529</td>
<td>0.509</td>
<td>0.531</td>
<td>1.000</td>
<td>0.000</td>
</tr>
</tbody>
</table>

FS: full states
FI: fixed inputs

Table 5.18: Maximum acceleration at the 37th floor.

<table>
<thead>
<tr>
<th>control strategy</th>
<th>X-direction</th>
<th>Y-direction</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>$\ddot{x}_{37}$ (mg)</td>
<td>reduction (%)</td>
</tr>
<tr>
<td>uncontrolled</td>
<td>70.8</td>
<td>46.3</td>
</tr>
<tr>
<td>viscous dampers</td>
<td>46.7</td>
<td>34.0</td>
</tr>
<tr>
<td>simulation 1</td>
<td>LQR</td>
<td>53.3</td>
</tr>
<tr>
<td></td>
<td>SOI-WNN</td>
<td>55.5</td>
</tr>
<tr>
<td></td>
<td>full states</td>
<td>55.5</td>
</tr>
<tr>
<td></td>
<td>fixed inputs</td>
<td>56.6</td>
</tr>
<tr>
<td>simulation 2</td>
<td>LQR</td>
<td>28.9</td>
</tr>
<tr>
<td></td>
<td>SOI-WNN</td>
<td>30.7</td>
</tr>
<tr>
<td></td>
<td>full states</td>
<td>32.9</td>
</tr>
<tr>
<td></td>
<td>fixed inputs</td>
<td>32.9</td>
</tr>
<tr>
<td>simulation 3</td>
<td>LQR</td>
<td>45.9</td>
</tr>
<tr>
<td></td>
<td>SOI-WNN</td>
<td>50.0</td>
</tr>
<tr>
<td></td>
<td>full states</td>
<td>53.1</td>
</tr>
<tr>
<td></td>
<td>fixed inputs</td>
<td>50.3</td>
</tr>
</tbody>
</table>
performance indices under various controllers. Fig. 5.25 illustrates the maximum inter-story displacements for the top 10 floors.

The main performance indices of interest are J1 and J2, which represent maximum inter-story displacement. We are also concerned by not increasing the acceleration in the structure (indices J3 to J5), as well as the base shear (index J6).

We first observe that the SOI-WNN does not mitigate as well as the LQR, and its performance mitigation at the damper locations is actually worst than the full-voltage case (ON). However, this is achieved with less than half the voltage required by the full-voltage strategy.

We are also comparing the SOI-WNN against the same algorithm without the forgetting capability inside impulse regions (NF). We observe that the performance is quite worst when the forgetting factor is left out of the algorithm. Fig. 5.25 shows the evolution of the network sizes under the forgetting and no forgetting features. Results show that in both cases, the network sizes evolves with the excitation. The no forgetting case keeps a larger network size over simulation time, as expected.

Furthermore, similarly to switching the forgetting feature off, switching the sliding controller off (NSC) results in worst mitigation. The fixed inputs (FI) strategy did not perform well. Lastly, all control strategies involving the MFD reduced the base shear by roughly 3-4%, while the viscous dampers did

![Figure 5.20](image)

Figure 5.20: Maximum 37th floor acceleration under time delay and random error. a) Random simulation 1; and b) random simulation 2.
Figure 5.21: Maximum acceleration profile, simulation 1: a) X-direction; and b) Y-direction.

Figure 5.22: Maximum acceleration profile, simulation 2: a) X-direction; and b) Y-direction.
Figure 5.23: Maximum acceleration profile in X-direction, simulation 3.

Table 5.19: Performance indices for earthquake mitigation (Imperial Valley), simulation 4.

<table>
<thead>
<tr>
<th>index</th>
<th>visc.</th>
<th>LQR</th>
<th>SOI</th>
<th>NF</th>
<th>FI</th>
<th>NSC</th>
<th>ON</th>
<th>OFF</th>
</tr>
</thead>
<tbody>
<tr>
<td>J1</td>
<td>0.722</td>
<td>0.617</td>
<td>0.697</td>
<td>0.744</td>
<td>0.735</td>
<td>0.735</td>
<td>0.718</td>
<td>0.935</td>
</tr>
<tr>
<td>J2</td>
<td>0.676</td>
<td>0.606</td>
<td>0.717</td>
<td>0.733</td>
<td>0.748</td>
<td>0.741</td>
<td>0.654</td>
<td>0.923</td>
</tr>
<tr>
<td>J3</td>
<td>0.964</td>
<td>0.930</td>
<td>0.940</td>
<td>0.943</td>
<td>0.943</td>
<td>0.939</td>
<td>0.933</td>
<td>0.955</td>
</tr>
<tr>
<td>J4</td>
<td>0.913</td>
<td>0.883</td>
<td>0.917</td>
<td>0.937</td>
<td>0.939</td>
<td>0.933</td>
<td>0.864</td>
<td>0.952</td>
</tr>
<tr>
<td>J5</td>
<td>0.895</td>
<td>0.940</td>
<td>0.971</td>
<td>1.008</td>
<td>1.014</td>
<td>0.976</td>
<td>0.955</td>
<td>0.983</td>
</tr>
<tr>
<td>J6</td>
<td>1.002</td>
<td>0.968</td>
<td>0.964</td>
<td>0.962</td>
<td>0.962</td>
<td>0.966</td>
<td>0.966</td>
<td>0.958</td>
</tr>
<tr>
<td>J7</td>
<td>0.613</td>
<td>0.854</td>
<td>0.891</td>
<td>0.898</td>
<td>0.881</td>
<td>0.877</td>
<td>0.975</td>
<td>0.156</td>
</tr>
<tr>
<td>J8</td>
<td>0.493</td>
<td>0.792</td>
<td>0.815</td>
<td>0.787</td>
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NF: no forgetting allowed  
FI: fixed inputs  
NSC: no sliding controller
not help.

From the results that we have obtained by revisiting simulation 4, the reader must surely wonder if the performance is earthquake-dependant. In the next subsection, we subject the structure to 29 additional earthquakes of different types. We keep all the parameters constant and scale the earthquake excitations to the same maximum acceleration (0.12 g).

5.6.2 All Earthquakes

Figs. A.1-A.30 and Tables A.2-A.31 in Appendix A show the maximum inter-story displacement profiles of the last 10 floors and the performance indices results for the 30 earthquakes respectively.

We start our analysis by looking at the mitigation performance results relative to the viscous damping strategy. We focus here on the J1 and J2 performance indices, which correspond to our main mitigation goals. Tables 5.20-5.21 list the relative performances for both J1 and J2 respectively, with the earthquake sorted by epicentral distance in ascendant order. Results smaller than 1 indicate an improved mitigation. We want examine the perfor-
CHAPTER 5. SIMULATIONS ON EXISTING STRUCTURE

Figure 5.25: Evolution of the network sizes. Forgetting versus no forgetting feature.

...mance of the SOI-WNN controller in function of such distance. For simplicity, we define near-field, mid-field, and far-field earthquakes purely on the epicentral distance. Remark that to be precise, such distinction should also be based on the maximum acceleration, frequency content, wave forms, etc. [31], and some of our earthquake would thus be qualified inappropriately. Instead, we allow those definitions to overlap, and define near-field as earthquake with epicentral distances from 0 to 20 km, mid-field from 15 to 55 km, and far-field from 50 km and up. Fig. 5.26 plots the relative performances.

Results from Fig. 5.26 show that the SOI-WNN controller does not perform well for structures that are very close to the epicenter (less than 5 km), here termed at-fault. However, for the near-field earthquakes further than 5 km and the mid-field earthquakes, the performance of the WNN-SOI are typically similar or better than both the LQR and passive-on strategies. Note that in some cases, the LQR and passive-on control cases dramatically under-perform the viscous strategy, in which cases the SOI-WNN always performs better. For the far-field earthquakes, the SOI-WNN performed the least, but its performance is yet close to the LQR and passive-on strategy when comparing results from the near-field and mid-field earthquakes.

We also examine the performance of the SOI-WNN controller against the
### 5.6. SOI-WNN - EARTHQUAKE EXCITATIONS

Table 5.20: Relative mitigation performance over viscous strategy for all earthquakes, J1.

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<th>NF</th>
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NF: no forgetting allowed  
FI: fixed inputs  
NSC: no sliding controller
## CHAPTER 5. SIMULATIONS ON EXISTING STRUCTURE

Table 5.21: Relative mitigation performance over viscous strategy for all earthquakes, J2.

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NF: no forgetting allowed  
FI: fixed inputs  
NSC: no sliding controller
Figure 5.26: Plots of the relative performance indices $J/J_{viscous}$: a) near-field, J1; b) near-field, J2; c) mid-field, J1; d) mid-field, J2; e) far-field, J1; and c) far-field, J2.
LQR controller in function of the average voltage effort. Fig. 5.27 shows the performance measures \( J_1 \times J_{10} \) and \( J_2 \times J_{10} \), for which a higher average use of voltage penalizes the performance measures \( J_1 \) and \( J_2 \). Results show that, except for a few cases, the SOI-WNN is more effective at inter-storey displacement mitigation.

Next, we study the performance of the SOI-WNN controller with respect to other configurations: no forgetting feature, a fixed input strategy, and no sliding controller. Table 5.22 displays the relative performance for the indices \( J_1 \) and \( J_2 \) with respect to the mitigation performance of the SOI algorithm. Once again, numbers below unity indicate an improved mitigation. Fig. 5.28 shows the distribution of the performance for all three cases.

We first take results from Figs. 5.28a-5.28b showing the mitigation performance without the forgetting feature. The distributions show no evidence that the forgetting feature improves the performance, despite that it is technically improving the stability of the controller. Even if the number of counts is in favor of using the feature, it appears that a few cases significantly improve the performance of the controller. However, if we go back to Table 5.28, we notice that using the forgetting feature improves the performance of both \( J_1 \) and \( J_2 \) indices 11 times on 30, versus 6 times on 30 without the feature. We further investigate the performance by looking at the average network size in Fig. 5.29. On average, network sizes are similar, except for four notable cases where ignoring the forgetting feature led to a significantly higher network size. It is the case for the Manjil, New Zealand, Norcia, and Victoria earthquakes. The Norcia and New Zealand earthquakes were cases for which excluding the forgetting feature led to a noticeably better mitigation performance for both \( J_1 \) and \( J_2 \) performance indices, and a significantly better performance for the \( J_2 \) index under the Victoria earthquake. For the other cases, including the forgetting feature led to similar performance. Thus, using the forgetting feature does improve stability and mitigation performance efficiency.

Next, Figs. 5.28c-5.28d illustrates the mitigation performance distribution against the fixed input strategy. Here, it is clear that the SOI-WNN improves the mitigation performance, sometimes dramatically compared to the fixed input case. Lastly, Figs. 5.28e-5.28f compares results for the sliding controller component. Here again, there is strong evidences that the sliding controller component does improve mitigation performances, as expected.
Figure 5.27: Mitigation performance and voltage: a) near-field, J1; b) near-field, J2; c) mid-field, J1; d) mid-field, J2; e) far-field, J1; and f) far-field, J2.
## CHAPTER 5. SIMULATIONS ON EXISTING STRUCTURE

Table 5.22: Relative mitigation performance over viscous strategy for all earthquakes, J2.

<table>
<thead>
<tr>
<th>earthquake</th>
<th>dist. (km)</th>
<th>J1/J1&lt;sub&gt;SOI&lt;/sub&gt;</th>
<th>J2/J2&lt;sub&gt;SOI&lt;/sub&gt;</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>NF</td>
<td>FI</td>
<td>NSC</td>
</tr>
<tr>
<td>Dinar</td>
<td>0.0</td>
<td>0.981</td>
<td>0.979</td>
</tr>
<tr>
<td>Erzican</td>
<td>0.0</td>
<td>1.004</td>
<td>0.983</td>
</tr>
<tr>
<td>Nahanni</td>
<td>0.0</td>
<td>1.016</td>
<td>1.063</td>
</tr>
<tr>
<td>San Fernando</td>
<td>0.0</td>
<td>1.016</td>
<td>1.054</td>
</tr>
<tr>
<td>Tabas</td>
<td>1.8</td>
<td>0.979</td>
<td>0.966</td>
</tr>
<tr>
<td>San Salvador</td>
<td>3.7</td>
<td>0.980</td>
<td>1.033</td>
</tr>
<tr>
<td>Kobe</td>
<td>7.1</td>
<td>1.008</td>
<td>1.003</td>
</tr>
<tr>
<td>Duzce</td>
<td>8.0</td>
<td>0.985</td>
<td>1.037</td>
</tr>
<tr>
<td>Parkfield</td>
<td>9.6</td>
<td>0.924</td>
<td>0.983</td>
</tr>
<tr>
<td>San Francisco</td>
<td>9.6</td>
<td>1.000</td>
<td>0.999</td>
</tr>
<tr>
<td>Coyote Lake</td>
<td>10.2</td>
<td>1.052</td>
<td>0.995</td>
</tr>
<tr>
<td>Imperial Valley</td>
<td>13.0</td>
<td>1.067</td>
<td>1.054</td>
</tr>
<tr>
<td>Victoria</td>
<td>13.8</td>
<td>1.005</td>
<td>0.955</td>
</tr>
<tr>
<td>Mammoth</td>
<td>14.3</td>
<td>0.998</td>
<td>0.992</td>
</tr>
<tr>
<td>Northridge</td>
<td>17.3</td>
<td>1.056</td>
<td>0.979</td>
</tr>
<tr>
<td>Irpinia</td>
<td>22.5</td>
<td>1.056</td>
<td>0.997</td>
</tr>
<tr>
<td>Spitak</td>
<td>24.0</td>
<td>1.030</td>
<td>1.015</td>
</tr>
<tr>
<td>Coalinga</td>
<td>30.3</td>
<td>1.009</td>
<td>1.022</td>
</tr>
<tr>
<td>Norcia</td>
<td>31.4</td>
<td>0.940</td>
<td>0.970</td>
</tr>
<tr>
<td>Friuli</td>
<td>49.1</td>
<td>0.932</td>
<td>1.118</td>
</tr>
<tr>
<td>Big Bear City</td>
<td>49.3</td>
<td>0.969</td>
<td>0.948</td>
</tr>
<tr>
<td>Manjil</td>
<td>50.0</td>
<td>1.024</td>
<td>1.015</td>
</tr>
<tr>
<td>Kern Country</td>
<td>56.0</td>
<td>1.006</td>
<td>0.988</td>
</tr>
<tr>
<td>Chi-Chi</td>
<td>59.0</td>
<td>1.001</td>
<td>0.994</td>
</tr>
<tr>
<td>Kocaeli</td>
<td>68.1</td>
<td>1.016</td>
<td>0.977</td>
</tr>
<tr>
<td>New Zealand</td>
<td>68.7</td>
<td>0.976</td>
<td>1.053</td>
</tr>
<tr>
<td>Loma Prieta</td>
<td>72.1</td>
<td>1.004</td>
<td>1.033</td>
</tr>
<tr>
<td>Gilroy</td>
<td>108.1</td>
<td>1.024</td>
<td>1.022</td>
</tr>
<tr>
<td>Michoagan</td>
<td>250.0</td>
<td>1.000</td>
<td>1.004</td>
</tr>
<tr>
<td>Denali</td>
<td>263.6</td>
<td>0.993</td>
<td>1.006</td>
</tr>
</tbody>
</table>

NF: no forgetting allowed  
FI: fixed inputs  
NSC: no sliding controller
Figure 5.28: Distributions of relative mitigation performances: a) $J_{1NF}/J_{1SOI}$; b) $J_{2NF}/J_{2SOI}$; c) $J_{1FI}/J_{1SOI}$; d) $J_{2FI}/J_{2SOI}$; e) $J_{1NSC}/J_{1SOI}$; and f) $J_{2NSC}/J_{2SOI}$.
Figure 5.29: Average network size with and without the forgetting feature: a) near-field; b) mid-field; and c) far-field.

5.7 SOI-WNN-Augmented LQR Controller

For our last section of the simulations, we would like to peek at the performance of an LQR controller augmented by the SOI-WNN. Essentially, we want to show capacity of our novel controller to improve a pre-designed controller. For the simulation, we will take an LQR controller which gain are computed based on some parametric properties estimation errors, similar to the numerical example given in Section 1.3.1. We study the performance for two cases.
Figure 5.30: Performance of various controllers in function of estimation errors on the fundamental frequency, wind excitation. a) J3; b) J4; and c) J5.

First, we look at the performance for wind mitigation. We will repeat simulation 2 in the X-direction, which consists of replacing the existing damping strategy with MFDs of similar capacity. We use that simulation because of the wider dynamic range of the device, which will help us to get more distinct results as we alter the parametric properties estimation error.

Second, we note the under-performance of the controller for the Michoagan (Mexico City) earthquake, and study if the hybrid controller would be capable of better performance. We anticipate that adding the SOI-WNN to the LQR would improve the performance.
5.7.1 Wind Excitation

Fig. 5.30 shows the results for performance indices J3 to J5, which are the primary control goals.

Results from performance indices J3 and J5 show that the LQR controller performance degrades with an overestimation of the fundamental frequency. The addition of the SOI-WNN to the LQR controller for those indices improves the performance for underestimation of the natural frequency, but has worst performance when the fundamental frequency is overestimated. Interestingly, the hybrid controller does not over-perform the SOI-WNN by itself.

Results from the J4 index show the LQR controller to be generally better than the hybrid controller, or than the SOI-WNN alone. However, the J4 index is the maximum acceleration at the location of the damping devices. Thus, a worst performance of the J4 index may signify a more aggressive control rule where the voltage follows more of a bang-bang rule type. Thus, we look at the performance indices J1 and J2, to verify if a more aggressive control rule also results in a better inter-story displacement mitigation. Fig. 5.30 shows the mitigation performance for indices J1 and J2. We note a better performance of the hybrid controller and the SOI-WNN controller alone for the J2 index, which corresponds to the inter-story displacements at the location of the damping devices. Indeed, the more aggressive control rule resulted in a better inter-story displacement mitigation at the expense of worst acceleration mitigation.

5.7.2 Earthquake Mitigation

Fig. 5.32 shows the results for the J1 and J2 indices, which are the primary control goals for mitigating the Michoacan (Mexico City) earthquake.

We remark a degradation of mitigation performance of the LQR controller with an underestimation of the fundamental frequency. The addition of the SOI-WNN to the LQR controller improves the performance over all ranges of estimation errors. The hybrid controller is also shown to be significantly better than the SOI-WNN controller alone.
5.7. **SOI-WNN-AUGMENTED LQR CONTROLLER**

![Graph](image)

**Figure 5.31:** Performance of various controllers in function of estimation errors on the fundamental frequency, wind excitation, J1 and J2.

![Graph](image)

**Figure 5.32:** Performance of various controllers in function of estimation errors on the fundamental frequency, earthquake excitation, J1 and J2.
5.8 Conclusion

In this chapter, we have simulated the proposed MFD on an existing structure located in Boston, MA, as an hypothetical replacement to the conventional viscous damping strategy. We have also integrated the SOI-WNN controller to verify its performance at mitigating wind loads and earthquake excitations. That was achieved after studying the non-adaptive parameter sensitivity using an harmonic excitation. Finally, we have given the reader a quick peek at the possibility of an hybrid controller comprising an LQR controller added to the proposed SOI-WNN controller. Results obtained in this chapter will be discussed thoroughly in the upcoming chapter.
Discussion on Results and Impacts
CHAPTER 6. DISCUSSION ON RESULTS AND IMPACTS

6.1 Introduction

In this chapter, we will discuss the various impacts of our proposed closed-loop control system. As we have mentioned in Section 1.4, we claim that the thesis makes several contributions to the field of structural control by proposing a closed-loop control system for large-scale systems with large uncertainties. Specifically, the MFD contributes to the subfield of mechanical damping devices. Its impacts will be discussed in Section 6.2. In addition, the SOI-WNN controller contributes to the subfield of intelligent control. Its impact will be discussed in Section 6.3. Lastly, the full closed-loop system, which consists of the MFD controlled with the SOI-WNN, contributes to the subfield of effective structural systems. Its impacts will be discussed in Section 6.4. The chapter will be concluded in Section 6.5.

6.2 Mechanical Damping Devices

We have proposed a new mechanical damping device designed using existing reliable and mechanically robust technologies. The device is, theoretically, a variable friction device capable of high damping force with low power requirement. Table 6.1 lists a comparison of variable friction devices proposed in the literature. To the best of our knowledge, the damping capacity of our device outperforms any other variable friction device with at least a factor of 10. The main impact of such mechanical device is its direct applicability to control of large-scale structures, because it is reliable, robust, and capable of large damping forces. In addition, we anticipate that the production cost of such device would be significantly lower than current MR dampers, and could even be as cheap as viscous strategies.

The first set of simulations from Chapter 5 demonstrated the capability of the MFD. Here, we wanted to verify that the MFD is theoretically capable of replacing an MR damper, and also could outperform an existing passive damping strategy.

Results from the wind simulations (simulations 1-3) show that a 200 kN MFD, designed to appropriately work on two 12-volts batteries, did not outperform the viscous strategy. We investigated further, looked at the hypothetical replacement of viscous dampers with MFDs of similar capacity, and we were able to show that our novel mechanical device was capable of outperforming the existing viscous strategy, with only a third of the dampers.
6.3. INTELLIGENT CONTROL

Table 6.1: Comparison of large-scale variable friction devices.

<table>
<thead>
<tr>
<th>authors</th>
<th>friction mechanism</th>
<th>force capacity (kN)</th>
<th>voltage range (v)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Yang &amp; Agrawal (2002) [212]</td>
<td>electro-magnetic</td>
<td>10</td>
<td>N/A</td>
</tr>
<tr>
<td>Durmaz et al. (2002) [44]</td>
<td>piezo-electric</td>
<td>0.9-11</td>
<td>N/A</td>
</tr>
<tr>
<td>Chen &amp; Chen (2004) [32]</td>
<td>piezo-electric</td>
<td>0.8</td>
<td>0-1000</td>
</tr>
<tr>
<td>Xu &amp; Ng (2008) [210]</td>
<td>piezo-electric</td>
<td>0.340</td>
<td>0-150</td>
</tr>
<tr>
<td>Zhao &amp; Li (2010) [227]</td>
<td>piezo-electric</td>
<td>3</td>
<td>0-120</td>
</tr>
<tr>
<td>Laflamme et al. (2011) [98]</td>
<td>drum brake</td>
<td>0-100</td>
<td>0-12</td>
</tr>
</tbody>
</table>

Interestingly, the full voltage (passive-on) strategy showed to outperform all control strategies in the wind simulations, but the simulations did not take into consideration static friction, and a passive-on type application would certainly cause high increases of temperature in the shoes. Perhaps, in this case, a simple bang-bang controller could be considered based on temperature and local velocity feedback, which would attempt to mimic the passive-on strategy.

The earthquake simulation (simulation 4) showed that the MFD outperformed the viscous strategy using semi-active devices of similar capacity. Moreover, we have shown excellent mitigation in one direction using an LQR controller, in which the devices controllability was of higher range.

The MFD is therefore a promising semi-active device for control of large-scale systems.

6.3 Intelligent Control

In the thesis, we have presented an online sequential intelligent controller. It consists of a wavelet neurocontroller, with the SOI algorithm for input selection. Table 6.2 lists the latest advances in online sequential controllers applied to large-scale systems. As shown in the evolution, the controller by Suresh et al. [181] is listed as the first to use an online mechanism for the hidden layer selection process. It is perhaps the earliest applicable online control scheme that necessitates limited prior training. Looking at the input selection side, Jung et al. [81] discussed the idea to use a Kalman filter for selecting modal inputs in order to ease the input selection process. The issue
CHAPTER 6. DISCUSSION ON RESULTS AND IMPACTS

Table 6.2: Comparison of online sequential intelligent controllers.

<table>
<thead>
<tr>
<th>authors</th>
<th>hidden layer selection</th>
<th>adaptation mechanism</th>
<th>activation function</th>
<th>semi-active application</th>
<th>input selection</th>
</tr>
</thead>
<tbody>
<tr>
<td>Lee et al. (2006) [100]</td>
<td>offline</td>
<td>cost</td>
<td>NN-N/A</td>
<td>MR</td>
<td>fixed</td>
</tr>
<tr>
<td>Jung et al. (2007) [81]</td>
<td>offline</td>
<td>cost</td>
<td>NN-N/A</td>
<td>MR</td>
<td>fixed-modal</td>
</tr>
<tr>
<td>Suresh et al. (2008) [181]</td>
<td>SOM</td>
<td>BP</td>
<td>NN-GRF</td>
<td>none</td>
<td>fixed</td>
</tr>
<tr>
<td>Laflamme &amp; Connor (2009) [95]</td>
<td>SOM</td>
<td>BP</td>
<td>NN-GRF</td>
<td>MR</td>
<td>fixed</td>
</tr>
<tr>
<td>Laflamme et al. (2009) [99]</td>
<td>SOM</td>
<td>BP</td>
<td>NN-WNN</td>
<td>MR</td>
<td>fixed</td>
</tr>
<tr>
<td>Laflamme et al. (2011) [97]</td>
<td>SOM</td>
<td>BP</td>
<td>NN-WNN</td>
<td>MR</td>
<td>fixed-limited</td>
</tr>
<tr>
<td>Laflamme &amp; Connor (2010) [96]</td>
<td>SOM</td>
<td>BP</td>
<td>NN-WNN</td>
<td>MFD</td>
<td>SOI</td>
</tr>
</tbody>
</table>

of input selection was later discussed in Laflamme et al. [97], where the algorithm used local measurements only. The inputs, however, were fixed. We have later proposed a fully variable local input selection process, the SOI algorithm.

In Chapter 3, we have presented that new strategy for online and sequential system identification and control of nonstationary systems. This is a non-trivial task, because the adaptation needs to be achieved quickly, without prior knowledge or training. Simulations have demonstrated the promising capabilities of the SOI algorithm. Specifically, we have shown that using the SOI algorithm led of a much better convergence than any fixed input strategy for tracking a function. That was mainly because the self-organizing input space was capable of accounting for changes in the system’s dynamic. The example showed that, not only the SOI algorithm was particularly helpful for selecting inputs when a time series cannot be analyzed a priori, the SOI algorithm might after all be the best option.

We have also looked in Chapter 3 at the cases of active control (regularization of a 3 DOF system), and at step-ahead neuro-prediction of chaotic excitations. The case of active control demonstrated that the SOI algorithm is stable, and that its performance is very close to a pre-optimized fixed inputs strategy. The step-ahead neuro-prediction showed the limitations of the algorithm for impulsive excitations. Such limitations could have been hypothesized, as the promise of the algorithm is for sequential online identification, which is a very complex task in the case of near-field earthquake excitations. That has been verified later in the main simulations with the earthquake excitations: the algorithm was not capable to perform well for at-fault earthquakes (San Fernando, for instance).

We were therefore capable of developing an algorithm that analyzes parts
of a time series online, and sequentially determines how to modify the input space for a better representation of the system’s dynamics. The proposed method has two fundamental engineering impacts. First, it has the capacity to use only a few observations to define a dynamic system. It can therefore be directly utilized for control of systems with limited measurements, or decentralized control schemes, just like we did when we have implemented the SOI algorithm with our WNN controller in the closed-loop control system. As we will discuss later in this section, such controller performed quite well using local measurements only. Second, it allows the engineer to take the input selection process out of the design process. Input selection, in the field of structural control, is often done heuristically. Now, we can use an algorithm that will build the input space sequentially, which has the tremendous advantage to have black-box models that utilizes efficient dynamic representation via the input space. We have demonstrated that this efficient representation led to more efficient networks, thus leaner and quicker controllers.

6.3.1 Controller Parameters

The intelligent controller that we have proposed is a form of neural network, and does not necessitate prior knowledge of the controlled structure. One of the major disadvantages of neurocontrollers is their numerous parameters that have to be tuned in order to function efficiently. In the thesis, we have tried to leave those parameters untouched for all simulations, and gave arguments or appropriate methods for their selections, as demonstrated in Section 5.4.

For the novel controller, Chapter 2 proposed an adaptive WNN in lieu of a conventional, non-adaptive, WNN. Chapter 3 took it further by introducing the SOI algorithm to create the SOI-WNN. We can see that evolution as the automation of some of the neural network processes in order to obtain a wider range of applicability, which in turn should enhance the applicability of structural control. The problem with such automation is that, at each stage, we have created additional parameters to be tuned. For instance, making the WNN adaptive included a self-organizing mapping (SOM) method. Then, adding the SOI layer added the necessity to tune the embedding technique. Nevertheless, we here argue that those added parameters are in fact making implementation easier, that the new parameters are easier to tune or select. Table 6.3 compares parameter selections between a classic non-adaptive WNN, the WNN, and the SOI-WNN. The adaptive WNN automates the selection
of the number of nodes (and their locations, incidently), but creates a new full set of parameters under the SOM method. The SOI-WNN does simplify the design of the sliding surface and automates input selection, but adds a new set of parameters under the SOI method.

Specifically, if we take the SOM method, its main benefit is that the network will only be defined in the region of the function. Thus, a pre-defined network lattice does not have to be designed, which results in a significantly leaner network, but the trade-off is that the network resolution, the pruning thresholds, and the minimum nodal distances need to be pre-defined. As we have discussed in Section 5.4, those values can be easily assigned, provided that we can normalize the inputs to a magnitude of $10^{-1}$. Thus, knowledge of the maximum magnitude of inputs is necessarily. Nevertheless, it can be assumed that such information can easily be determined by an engineer. It is sensibly the same concept for the SOI algorithm. Instead of have to pre-determine the type, lag, and embedding dimension of inputs, which has been shown to be a non-trivial task that may lead to network inefficiencies, we have automated the process with an algorithm that needs internal parameters for the MI and FNN tests. However, we have argued that those parameters can be loosely pre-selected with little consequences.

Table 6.3: Neurocontroller parameters for a feedforward single-layer wavelet neural network.
Finally, we have concluded the parameter sensitivity analysis by verifying the sensitivity of the controller itself to noise in the measurements and delay in the control device. The SOI-WNN was remarkably capable to perform well with respect to noise, and it took a great delay (1000 ms) to induce a significant change in the performance.

Thus, we have developed an intelligent, or automatic/adaptive, controller for uncertain systems. The direct impact of such automation is a wider range of applicability of the controller. Effectively, the algorithm can easily adapt to different dynamics. In addition, the engineering parametrization of the algorithm has been simplified, and we have given in Table 5.11 a method for selecting non-adaptive parameters. The controller, by its automation, offers an improved efficiency of vibration mitigation as we will see in the next subsection.

6.3.2 Closed-Loop System Performance

Wind Excitation

In Chapter 5, we have conducted several simulations to assess the performance of the SOI-WNN controller. The first set of simulations was conducted with a wind excitation. We have basically revisited the first three simulations (simulations 1-3) conducted to verify the performance of the MFD, and looked at the relative performance of the controller with respect to a full feedback controller (LQR).

Overall, the SOI-WNN compared very well against a full feedback controller. We have seen that the controller performance was constantly close to the LQR performance (within ±4.1% of the total mitigation). Thus, we have designed a controller which, without knowledge of parametric properties and using local measurements only, was capable of comparing with a full state feedback LQR controller. Also, remarkably, the SOI-WNN did a better utilization of the control devices than the LQR case: less voltage for a similar or better mitigation.

We have also verified the relative performance of the SOI-WNN with respect to a fixed inputs strategy and a full state strategy. Results showed that the SOI-WNN typically performed similarly (and sometimes better) than the two other strategies. Thus, the SOI algorithm is an effective way to control with limited measurements.

In addition, we were interested in the full closed-loop performance. We
have often compared with the passive-on control case, which assumes that the MFD works at full capacity, which ignored static friction. Interestingly, the passive-on case performed better at acceleration mitigation, except for the specific case of the hypothetical 1350 kN MFD replacing the current viscous strategy (simulation 2, X-direction), which had a wider range of controllability. For that specific case, the SOI-WNN performed significantly better. Furthermore, the SOI-WNN allowed good acceleration mitigation with only approximately 50% of the voltage required for the passive-on case. The closed-loop system has shown to be a very effective way to mitigate wind vibrations. Thus, the controller is well suited for wind mitigation applications.

6.3.3 Earthquake Excitation

We have begun our earthquake simulations with the Imperial Valley earthquake in order to revisit the previous simulation done with the MFD. Results showed that the SOI-WNN was not capable of performing as well as the LQR controller at displacement mitigation, and did approximately as well as the passive-on case with less than half of the voltage. What is interesting from the simulation results is that the exclusion of the forgetting capacity of the WNN has significant negative consequences, so does the exclusion of the sliding control mechanism. In addition, the SOI-WNN did much better than the fixed input strategy. It was also demonstrated that the forgetting feature does lead to a more efficient size of the representation.

We then furthered verifications by running simulations on 29 additional earthquakes of different intensities and epicentral locations. Results showed that the SOI-WNN performed very well for near-field earthquakes located outside an approximate 5 km zone, and also for mid-field earthquakes. There was no improvements for the far-field earthquakes, but the mitigation performances compared well with the other controllers (LQR and passive-on). Furthermore, the investigation of the performance in function of voltage demonstrated that the SOI-WNN mitigates vibration in a more effective way than the LQR controller does. We also confirmed that the forgetting and sliding controller features improved mitigation efficiency, and that the SOI algorithm for input selection was a better option than a fixed-input strategy.

Therefore, we can conclude that the SOI-WNN performs very well at interstorey displacement mitigation. In addition, if we look at data from Appendix A, rarely the mitigation strategy worsens floor acceleration compared to the
uncontrolled case. When it does, it does not exceed 10% enhancement. From our results, we can deduce that earthquake applications include structures that are not located at-fault. It is a good strategy for far-field locations, but in the case where only earthquake mitigation is of concern, perhaps a viscous strategy might be more economical and efficient.

### 6.3.4 SOI-WNN-Augmented LQR Controller

We have concluded our main simulation results by a quick demonstration of the SOI-WNN capacity to improve an LQR controller designed based on wrong estimations of dynamic parameters. The purpose of the subsection was simply to give an idea of the possibility of the controller. We have shown, without surprise, that the algorithm is generally capable of improving the performances of an LQR controller. However, what was interesting is that the SOI-WNN-augmented LQR controller was not capable of outperforming the SOI-WNN by itself for wind mitigation. It was also capable of improving the performance of an LQR controller in the case of the Michigan earthquake. A main advantage of using the SOI-WNN for a hybrid controller can be in the enhanced mathematical tractability. For instance, one can be nervous using an SOI-WNN as a sole controller, because the inherent black-box model fails at giving intuitive results. Instead, an LQR controller, for example, could be used to place the eigenvalues of the estimated system, and the SOI-WNN taken as a strategy to enhance mitigation performances.

### 6.4 Effective Structural Systems

We have demonstrated in the simulations that the integrated MFD-SOI-WNN closed-loop control system is an effective way to mitigate structural vibrations, whether they are induced by moderate-to-high winds or earthquakes. The control system is capable of mitigation over a wide bandwidth of excitations, with limited power input, which results in a more effective structural system.

As structural engineers, we primarily foresee semi-active and active control strategies as an effective way to enhance safety and serviceability of civil structures. Nevertheless, we can realistically think that one of the main arguments that would dramatically enhance acceptability of semi-active and active structural control in the construction and civil engineering fields is the economic potential of such systems. The problem is that we only have a
few applications in the world. For instance, there is approximately 70 active and semi-active applications in Japan as of 2007 [73], which counts most of the world-wide applications. Therefore, it is very hard to estimate the total savings related to semi-active or active control.

The economies related to passive control have already been discussed in several research papers, and it is easy to show that a more flexible structure is cheaper to construct that a stiff structures because of the savings on material. For instance, take the Citigroup Tower in New York City, NY. It was equipped with a TMD in 1977. Structural engineers have evaluated savings to be in the order of 3.5 to 4 millions of dollars (in 1977 money) arising from the economy of 2000 tons of structural steel needed to satisfy deflection constraints [40]. In addition, Hongnan & Linsheng [67] have taken statistics from 30 base-isolated buildings located in China, and concluded that the utilization of base isolation systems led to savings on the order of 3% to 15%. Furthermore, Chen [34] established that the use of viscous dampers in the Pangu Plaza located in Beijing, China, has resulted in savings on the order of 2 to 7 millions RMB (approximately 0.3 to 1.05 millions USD).

Nevertheless, when it comes to semi-active systems, the only information that we can easily harvest in the literature is principally the economy on the TMD weight when using an hybrid semi-active or active TMD system. For instance, Lindh et al. [112] have numerically demonstrated that the use of a semi-active system with a TMD can save up to 50% of the total weight of the TMD system. Fig. 6.1 shows the effective damping $\xi_e$ versus different mass ratio $\mu = m/M$ where $m$ is the mass of the TMD and $M$ is the mass of the structure. The semi-active strategies, where VO-STMD and MFD-STMD respectively refer to a continuously variable orifice damper and an MFD controlling a TMD, give a significantly better damping performance than a passive TMD. Thus, take the passive TMD system installed in the John Hancock tower in Boston, MA. It consists of two lead and steel masses of 270 000 kg installed at the top of the tower. We can conservatively take a price for lead of 2 USD/kg, and compute savings of 540 000 USD arising from the utilization of a semi-active device! This certainly outweighs the cost of a semi-active device (200 kN MR dampers are on the order of 25 000 USD), plus the cost of the controller, maintenance, and electricity over a 50 years life-time.

Furthermore, if we look at the results from our simulations, we show that it was theoretically feasible to cut the number of damping devices from 60 to 40 by using MFDs. As an exercise, we compute the potential theoretical
6.5. CONCLUSION

Figure 6.1: Mass ratio versus effective damping for two STMDs and a TMD [112].

savings from using our semi-active damper. We assume that each viscous damper costs 5 000 USD, and we replace the viscous dampers by MFDs in the X-direction. We take two different approaches: in the first one, we assume that the braces in both directions are approximately the same cost (despite that the toggle braces are more complex, they are smaller that the normal braces). In the second approach, we stay more conservative: we assume that the toggle braces are 50% more expensive than the normal braces, and that the large MFDs, including controllers, are 15 000 USD each. Table 6.4 shows the results. We find that, in the X-direction, theoretical economical benefits of our strategy ranges between 200 000 USD and 300 000 USD, which represents 20%-30% savings on the cost of the existing viscous damping strategy.

6.5 Conclusion

In this chapter, we have discussed results obtained from our simulations. We have listed the main contributions, impacts, and applications of the MFD, the SOI-WNN, and the MFD-SOI-WNN integrated control system. We have discussed major mechanical, technical, and economical considerations that
CHAPTER 6. DISCUSSION ON RESULTS AND IMPACTS

Table 6.4: Cost analysis of passive viscous versus MFD control strategies

<table>
<thead>
<tr>
<th>Damping Strategy</th>
<th>Direction</th>
<th>Number of Devices</th>
<th>Device Cost (1000 USD)</th>
<th>Brace Cost (1000 USD)</th>
<th>Total (1000 USD)</th>
</tr>
</thead>
<tbody>
<tr>
<td>viscous</td>
<td>X</td>
<td>30</td>
<td>5</td>
<td>11.5</td>
<td>990</td>
</tr>
<tr>
<td></td>
<td>Y</td>
<td>30</td>
<td>5</td>
<td>11.5</td>
<td>975</td>
</tr>
<tr>
<td>viscous (conservative)</td>
<td>X</td>
<td>30</td>
<td>5</td>
<td>9</td>
<td>975</td>
</tr>
<tr>
<td></td>
<td>Y</td>
<td>30</td>
<td>5</td>
<td>13.5</td>
<td>975</td>
</tr>
<tr>
<td>MFD</td>
<td>X</td>
<td>10</td>
<td>10</td>
<td>11.5</td>
<td>710</td>
</tr>
<tr>
<td></td>
<td>Y</td>
<td>30</td>
<td>5</td>
<td>11.5</td>
<td>710</td>
</tr>
<tr>
<td>MFD (conservative)</td>
<td>X</td>
<td>10</td>
<td>15</td>
<td>9</td>
<td>795</td>
</tr>
<tr>
<td></td>
<td>Y</td>
<td>30</td>
<td>5</td>
<td>13.5</td>
<td>795</td>
</tr>
</tbody>
</table>

makes our contributions promising for future applications. The proposed mechanical device, controller, and control system has been shown to be theoretically remarkably great at mitigating wind- and most earthquake-induced vibration. The next chapter concludes the thesis.
Conclusion
CHAPTER 7. CONCLUSION

In this thesis, we have presented a fully integrated closed-loop control system for large-scale systems with large uncertainties. The main objective is to enhance the acceptability of semi-active control systems into civil structures, in order to create more effective structural systems.

We have started the thesis by describing a robust control algorithm, which could efficiently mitigate vibrations of large-scale systems with full uncertainties on the parametric properties. In Chapter 2, we have presented a modified version of neurocontrollers for systems equipped with semi-active control devices. In Chapter 3, we have improved the algorithm with the SOI algorithm for systems equipped with limited sensors, thus a controller using local measurements only. In Chapter 4, we have proposed a novel semi-active damping device with enhanced mechanical reliability for large-scale damping. In Chapter 5, we have simulated the integrated closed-loop system on an existing structure located in Boston, MA. In Chapter 6, we have discussed the simulation results and demonstrated that the proposed system was a very effective way of mitigating vibrations in large-scale systems with large uncertainties.

It is now time to conclude, and we do so by summarizing the main contributions and impacts of the research in Section 7.1, and discuss limitations and future work in Section 7.2.

7.1 Summary of Contributions & Impacts

We here list our main contributions and impacts of the research, divided in three categories: the MFD, the intelligent controller, and the integrated MFD-SOI-WNN control system.

7.1.1 Modified Friction Device

The major contributions and impacts of the MFD are listed as follows.

- Very high damping capacity with low power input

The MFD is capable of very large variable friction capacity, in the order of $10^5$ N, on a 12-volts battery. This is 10 times the current capacities reported in the literature. This significantly improved capacity arises from the use of the self-energizing capacity of drum brakes.
7.1. SUMMARY OF CONTRIBUTIONS & IMPACTS

- Enhanced applicability of semi-active dampers

The MFD has an enhanced applicability compared to other semi-active devices, such as MR dampers, because it is designed based on robust and reliable mechanical technology.

7.1.2 Intelligent Controller

The major contributions and impacts of the SOI-WNN are listed as follows.

- Dynamic hyperspace for constructing representations

The idea of a dynamic hyperspace, the SOI algorithm, is to the best of our knowledge the first automated sequential input selection process.

- More effective control with limited local measurements

The SOI algorithm is based on the utilization of local state observations for representing the system dynamics. It allows control with limited, or local, state measurements.

- Automated input selection

The SOI algorithm is a method that allows automated input selection. Thus, the selection of inputs for black-box systems is taken out of the design process.

- Improved convergence and efficiencies of black-box models

We have demonstrated that the use of the SOI algorithm may led to significantly improved convergence, and also to more efficient representations.

- Wider range of applicability of the controller

We have shown that the controller was capable of adapting to different dynamics, which was made possible by automating most features of the intelligent controller. Therefore, the controller has a wider range of applicability.
7.1.3 Integrated Control System

The major contributions and impacts of the integrated control system MFD-SOI-WNN are listed as follows.

- Enhanced applicability and acceptability of semi-active control systems

  We have presented a robust closed-loop control system that does not need prior training. By addressing the problems of parametric uncertainties, limited measurements, and large actuation on low power, the proposed control strategy is applicable, which should enhance the acceptance of semi-active control systems for large-scale structures.

- Enhanced mitigation of wind-induced vibrations

  Results from the simulations have shown that the proposed system is capable of mitigating wind vibrations effectively.

- Enhanced mitigation of earthquake-induced vibrations, for near-field and mid-field earthquake zone, except at-fault

  Results from the simulations have shown that the proposed system is capable of mitigating earthquake vibrations effectively for structures located in near-field and mid-field zone, except for a small region around the epicenter. They also do well for far-field zones, but they do not offer particular advantages compared to passive strategies.

- Economically viable structural systems

  The short economic study that we have provided in the last chapter has demonstrated that the proposed control strategy may lead to significant savings by creating a more effective structural system.

7.2 Limitations and Future Work

7.2.1 Modified friction device

The main limitation of the friction device is in its dynamic model. We have attempted to model the hysteresis behavior as accurately as possible, but to the
7.2. LIMITATIONS AND FUTURE WORK

best of our knowledge, no research has been done on the large scale hysteresis behavior of cast-iron on cast-iron at low frequency and high magnitude. We have based our model on an existing large-scale damper behaving in a friction mode for small magnitude, but the test was not frequency-dependant. We have also scaled the model parameters based on a research of cast-iron friction at a higher frequency, which was the closest data to our device that we were able to find in the literature.

It is therefore fundamental to experimentally verify the large-scale frictional behavior of the MFD. As this thesis is being written, a 50 kN friction prototype is being constructed at MIT in order to examine its frictional behavior. Later, its capacity will be increased to 200 kN, and the stiffness and viscous elements added in order to create the MFD. This experimental study will be essential for demonstrating the theoretical capacity of the novel friction device.

7.2.2 Intelligent Controller

The first limitation of the proposed intelligent controller is the numerous non-adaptive parameters to be selected. As we have previously discussed, by adding the SOM and SOI algorithms to create the adaptive controller that needs no prior training, we have actually added layers of non-adaptive parameters. Thus, this is not a magic solution that could apply to any system; some design will be necessary. Nevertheless, we have argued that the selection of those parameters is significantly easier to achieved than for traditional neurocontrollers. For instance, the number of functions in the hidden layer and the inputs are quite difficult to design for.

In addition, we have ignored the controller delay. Instead, we assumed some larger delay in the actuator, and demonstrated that the controller was robust under 1 second of delay. Some prior tests with the code has shown that the algorithm was capable of running under 20 ms per time step, but that including the model simulation time, and excluding the sensor dynamics and the possibility of witting a more efficient code with a platform faster than MATLAB. As a future step, it would be interesting to include the sensor dynamics and fully assess the impact of the controller delay.
7.2.3 Integrated Control System

An interesting result from the simulations was that the passive-on control case, which consists of the device set to its maximum voltage at any time, performed quite well at wind mitigation. There was some issues in simulating such control scheme. We have not modeled the static friction, and excluded the temperature effect on the hysteresis behavior, which should be quite important in the case where the braking shoes are locked on the drum. The reason we have not done so is that we assumed the possibility of designing a controller, such as a bang-bang controller, that would make the brake behave in a passive-on mode. It would be interesting to design such controller that would theoretically be based on local measurements, and analyze its performance with respect to the SOI-WNN, while including the voltage delay and the mitigation performance with respect to voltage usage. A passive-on strategy based on a bang-bang controller might be more acceptable by the engineering field because of the enhanced mathematical tractability compared to neural networks.

Furthermore, the economic argument presented in the last chapter could be extended using more accurate data regarding the cost of maintenance, materials, controller, and energy. Rigorous economic studies of the benefits of semi-active control systems are vital steps towards enhanced acceptability and implementations.
Supplemental Earthquake Simulation Results
## APPENDIX A. SUPPLEMENTAL EARTHQUAKE SIMULATION RESULTS

### Supplemental Earthquakes

Table A.1: List of simulated earthquakes.

<table>
<thead>
<tr>
<th>Location</th>
<th>Year</th>
<th>Station</th>
<th>Angle (deg)</th>
<th>Dist. (km)</th>
<th>Mechanism</th>
<th>Mag. (RS)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Big Bear City, CA</td>
<td>2003</td>
<td>Morongo Valley</td>
<td>90</td>
<td>49.3</td>
<td>strike-slip</td>
<td>4.92</td>
</tr>
<tr>
<td>Chi-Chi, Taiwan</td>
<td>1999</td>
<td>CHY012</td>
<td>00</td>
<td>59.0</td>
<td>reverse-oblique</td>
<td>7.62</td>
</tr>
<tr>
<td>Coalinga, CA</td>
<td>1983</td>
<td>Parkfield - Fault Zone 10</td>
<td>00</td>
<td>30.3</td>
<td>reverse</td>
<td>6.36</td>
</tr>
<tr>
<td>Coyote Lake, CA</td>
<td>1979</td>
<td>Gilroy Array #1</td>
<td>230</td>
<td>10.2</td>
<td>strike-slip</td>
<td>5.74</td>
</tr>
<tr>
<td>Denali, Alaska</td>
<td>2002</td>
<td>Anchorage - K2-03</td>
<td>090</td>
<td>263.6</td>
<td>strike-slip</td>
<td>7.90</td>
</tr>
<tr>
<td>Dinar, Turkey</td>
<td>1995</td>
<td>Dinar</td>
<td>090</td>
<td>0.0</td>
<td>normal</td>
<td>6.4</td>
</tr>
<tr>
<td>Duzce, Turkey</td>
<td>1999</td>
<td>Lamont 531</td>
<td>090</td>
<td>8.0</td>
<td>strike-slip</td>
<td>7.14</td>
</tr>
<tr>
<td>Erzican, Turkey</td>
<td>1992</td>
<td>Erzincan</td>
<td>090</td>
<td>0.0</td>
<td>strike-slip</td>
<td>6.69</td>
</tr>
<tr>
<td>Friuli, Italy</td>
<td>1976</td>
<td>Barcis</td>
<td>00</td>
<td>49.1</td>
<td>reverse</td>
<td>6.5</td>
</tr>
<tr>
<td>Gilroy, CA</td>
<td>2002</td>
<td>San Fran. - Fire Stn. #17</td>
<td>050</td>
<td>108.1</td>
<td>strike-slip</td>
<td>4.90</td>
</tr>
<tr>
<td>Imperial Valley, CA¹</td>
<td>1940</td>
<td>El Centro Array #9</td>
<td>180</td>
<td>13.0</td>
<td>strike-slip</td>
<td>7.0</td>
</tr>
<tr>
<td>Irpinia, Italy</td>
<td>1980</td>
<td>Brienza</td>
<td>00</td>
<td>22.5</td>
<td>normal</td>
<td>6.90</td>
</tr>
<tr>
<td>Kern County, CA</td>
<td>1952</td>
<td>Taft Lincoln School</td>
<td>111</td>
<td>56.0</td>
<td>reverse</td>
<td>7.36</td>
</tr>
<tr>
<td>Kobe, Japan</td>
<td>1995</td>
<td>Nishi-Akashi</td>
<td>090</td>
<td>7.1</td>
<td>strike-slip</td>
<td>6.9</td>
</tr>
<tr>
<td>Kocaeli, Turkey</td>
<td>1999</td>
<td>Ambarli</td>
<td>000</td>
<td>68.1</td>
<td>strike-slip</td>
<td>7.51</td>
</tr>
<tr>
<td>Loma Prieta, CA</td>
<td>1989</td>
<td>Oakland Title &amp; Trust</td>
<td>170</td>
<td>72.1</td>
<td>reverse-oblique</td>
<td>6.93</td>
</tr>
<tr>
<td>Mammoth Lakes, CA</td>
<td>1980</td>
<td>Long Valley Dam</td>
<td>000</td>
<td>14.3</td>
<td>strike-slip</td>
<td>5.69</td>
</tr>
<tr>
<td>Manjil, Iran</td>
<td>1990</td>
<td>Qazvin</td>
<td>066</td>
<td>050</td>
<td>strike-slip</td>
<td>7.37</td>
</tr>
<tr>
<td>Michoacan, Mexico</td>
<td>1985</td>
<td>Station 1</td>
<td>180</td>
<td>250⁠</td>
<td>reverse</td>
<td>8.1</td>
</tr>
<tr>
<td>Nahanni, Canada</td>
<td>1985</td>
<td>Site 2</td>
<td>240</td>
<td>0.0</td>
<td>reverse</td>
<td>6.76</td>
</tr>
<tr>
<td>New Zealand</td>
<td>1987</td>
<td>Marareni Primary School</td>
<td>040</td>
<td>68.7</td>
<td>normal</td>
<td>6.6</td>
</tr>
<tr>
<td>Norcia, Italy</td>
<td>1979</td>
<td>Bevagna</td>
<td>090</td>
<td>31.4</td>
<td>normal</td>
<td>5.90</td>
</tr>
<tr>
<td>Northridge, CA</td>
<td>1994</td>
<td>Santa Monica City Hall</td>
<td>090</td>
<td>17.3</td>
<td>reverse</td>
<td>6.69</td>
</tr>
<tr>
<td>Parkfield, CA</td>
<td>1966</td>
<td>Cholame #5</td>
<td>085</td>
<td>9.6</td>
<td>strike-slip</td>
<td>6.19</td>
</tr>
<tr>
<td>San Fernando, CA</td>
<td>1971</td>
<td>Pacoima Dam</td>
<td>164</td>
<td>0.0</td>
<td>reverse</td>
<td>6.61</td>
</tr>
<tr>
<td>San Francisco, CA</td>
<td>1957</td>
<td>Golden Gate Park</td>
<td>010</td>
<td>9.6</td>
<td>reverse</td>
<td>5.28</td>
</tr>
<tr>
<td>San Salvador, El Salv.</td>
<td>1986</td>
<td>National Geografical Inst</td>
<td>180</td>
<td>3.7</td>
<td>strike-slip</td>
<td>5.80</td>
</tr>
<tr>
<td>Spitak, Armenia</td>
<td>1988</td>
<td>Gukasian</td>
<td>000</td>
<td>24.0</td>
<td>reverse-oblique</td>
<td>6.77</td>
</tr>
<tr>
<td>Tabas, Iran</td>
<td>1978</td>
<td>Tabas</td>
<td>000</td>
<td>1.8</td>
<td>reverse</td>
<td>7.35</td>
</tr>
<tr>
<td>Victoria, Mexico</td>
<td>1980</td>
<td>Cerro Prieto</td>
<td>045</td>
<td>13.8</td>
<td>strike-slip</td>
<td>6.33</td>
</tr>
</tbody>
</table>

¹: repeated in the appendix for completeness

†: estimated and classified as far-field
A.1. BIG BEAR CITY 2003

A.1 Big Bear City 2003

Figure A.1: Big Bear City earthquake: a) time series (unscaled); and b) maximum inter-story displacements of the top 10 floors under various control strategies.

Table A.2: Performance indices, Big Bear City Earthquake, simulation 4.

<table>
<thead>
<tr>
<th>index</th>
<th>visc.</th>
<th>LQR</th>
<th>SOI</th>
<th>NF</th>
<th>FI</th>
<th>NSC</th>
<th>ON</th>
<th>OFF</th>
</tr>
</thead>
<tbody>
<tr>
<td>J1</td>
<td>0.612</td>
<td>0.558</td>
<td>0.587</td>
<td>0.568</td>
<td>0.556</td>
<td>0.563</td>
<td>0.908</td>
<td>0.915</td>
</tr>
<tr>
<td>J2</td>
<td>0.580</td>
<td>0.619</td>
<td>0.558</td>
<td>0.545</td>
<td>0.530</td>
<td>0.560</td>
<td>1.008</td>
<td>0.897</td>
</tr>
<tr>
<td>J3</td>
<td>0.985</td>
<td>0.965</td>
<td>0.986</td>
<td>0.974</td>
<td>0.992</td>
<td>0.982</td>
<td>0.967</td>
<td>0.992</td>
</tr>
<tr>
<td>J4</td>
<td>0.991</td>
<td>1.023</td>
<td>1.037</td>
<td>0.998</td>
<td>1.035</td>
<td>1.023</td>
<td>0.957</td>
<td>1.001</td>
</tr>
<tr>
<td>J5</td>
<td>1.013</td>
<td>1.056</td>
<td>1.050</td>
<td>1.053</td>
<td>1.035</td>
<td>1.053</td>
<td>1.119</td>
<td>0.999</td>
</tr>
<tr>
<td>J6</td>
<td>0.997</td>
<td>0.996</td>
<td>0.996</td>
<td>0.995</td>
<td>0.994</td>
<td>0.997</td>
<td>0.995</td>
<td>0.996</td>
</tr>
<tr>
<td>J7</td>
<td>0.434</td>
<td>0.866</td>
<td>0.848</td>
<td>0.864</td>
<td>0.755</td>
<td>0.840</td>
<td>0.968</td>
<td>0.091</td>
</tr>
<tr>
<td>J8</td>
<td>0.337</td>
<td>0.799</td>
<td>0.658</td>
<td>0.658</td>
<td>0.628</td>
<td>0.685</td>
<td>0.891</td>
<td>0.070</td>
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<tr>
<td>J9</td>
<td>0.000</td>
<td>0.613</td>
<td>0.882</td>
<td>0.880</td>
<td>0.888</td>
<td>0.777</td>
<td>1.000</td>
<td>0.000</td>
</tr>
<tr>
<td>J10</td>
<td>0.000</td>
<td>0.545</td>
<td>0.743</td>
<td>0.754</td>
<td>0.818</td>
<td>0.646</td>
<td>1.000</td>
<td>0.000</td>
</tr>
</tbody>
</table>

NF: no forgetting allowed
FI: fixed inputs
NSC: no sliding controller
APPENDIX A. SUPPLEMENTAL EARTHQUAKE SIMULATION RESULTS

A.2 Chi-Chi 1999

Figure A.2: Chi-Chi earthquake: a) time series (unscaled); and b) maximum inter-story displacements of the top 10 floors under various control strategies.

Table A.3: Performance indices, Chi-Chi Earthquake, simulation 4.

<table>
<thead>
<tr>
<th>index</th>
<th>visc.</th>
<th>LQR</th>
<th>SOI</th>
<th>NF</th>
<th>FI</th>
<th>NSC</th>
<th>ON</th>
<th>OFF</th>
</tr>
</thead>
<tbody>
<tr>
<td>J1</td>
<td>0.690</td>
<td>0.750</td>
<td>0.841</td>
<td>0.842</td>
<td>0.836</td>
<td>0.860</td>
<td>0.668</td>
<td>0.948</td>
</tr>
<tr>
<td>J2</td>
<td>0.800</td>
<td>0.761</td>
<td>0.862</td>
<td>0.863</td>
<td>0.871</td>
<td>0.883</td>
<td>0.772</td>
<td>0.946</td>
</tr>
<tr>
<td>J3</td>
<td>0.755</td>
<td>0.824</td>
<td>0.952</td>
<td>0.932</td>
<td>0.908</td>
<td>0.977</td>
<td>0.772</td>
<td>0.968</td>
</tr>
<tr>
<td>J4</td>
<td>0.838</td>
<td>0.856</td>
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<td>0.886</td>
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<td>0.890</td>
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</tr>
<tr>
<td>J5</td>
<td>0.686</td>
<td>0.732</td>
<td>0.817</td>
<td>0.828</td>
<td>0.827</td>
<td>0.839</td>
<td>0.627</td>
<td>0.939</td>
</tr>
<tr>
<td>J6</td>
<td>0.918</td>
<td>0.907</td>
<td>0.924</td>
<td>0.919</td>
<td>0.933</td>
<td>0.943</td>
<td>0.892</td>
<td>0.986</td>
</tr>
<tr>
<td>J7</td>
<td>1.000</td>
<td>1.132</td>
<td>1.021</td>
<td>1.068</td>
<td>1.051</td>
<td>0.947</td>
<td>1.168</td>
<td>0.415</td>
</tr>
<tr>
<td>J8</td>
<td>0.872</td>
<td>1.049</td>
<td>0.967</td>
<td>0.983</td>
<td>0.974</td>
<td>0.924</td>
<td>1.057</td>
<td>0.241</td>
</tr>
<tr>
<td>J9</td>
<td>0.000</td>
<td>0.776</td>
<td>0.532</td>
<td>0.566</td>
<td>0.519</td>
<td>0.394</td>
<td>1.000</td>
<td>0.000</td>
</tr>
<tr>
<td>J10</td>
<td>0.000</td>
<td>0.696</td>
<td>0.464</td>
<td>0.471</td>
<td>0.474</td>
<td>0.341</td>
<td>1.000</td>
<td>0.000</td>
</tr>
</tbody>
</table>

NF: no forgetting allowed
FI: fixed inputs
NSC: no sliding controller
A.3 Coalinga 1983

Figure A.3: Coalinga earthquake: a) time series (unscaled); and b) maximum inter-story displacements of the top 10 floors under various control strategies.

Table A.4: Performance indices, Coalinga Earthquake, simulation 4.

<table>
<thead>
<tr>
<th>index</th>
<th>visc.</th>
<th>LQR</th>
<th>SOI</th>
<th>NF</th>
<th>FI</th>
<th>NSC</th>
<th>ON</th>
<th>OFF</th>
</tr>
</thead>
<tbody>
<tr>
<td>J1</td>
<td>0.633</td>
<td>0.624</td>
<td>0.759</td>
<td>0.766</td>
<td>0.775</td>
<td>0.771</td>
<td>0.565</td>
<td>0.899</td>
</tr>
<tr>
<td>J2</td>
<td>0.729</td>
<td>0.776</td>
<td>0.790</td>
<td>0.797</td>
<td>0.797</td>
<td>0.795</td>
<td>0.772</td>
<td>0.908</td>
</tr>
<tr>
<td>J3</td>
<td>0.676</td>
<td>0.729</td>
<td>0.752</td>
<td>0.747</td>
<td>0.755</td>
<td>0.756</td>
<td>0.702</td>
<td>0.876</td>
</tr>
<tr>
<td>J4</td>
<td>0.882</td>
<td>0.874</td>
<td>0.890</td>
<td>0.904</td>
<td>0.907</td>
<td>0.915</td>
<td>0.857</td>
<td>0.963</td>
</tr>
<tr>
<td>J5</td>
<td>0.791</td>
<td>0.802</td>
<td>0.858</td>
<td>0.869</td>
<td>0.851</td>
<td>0.857</td>
<td>0.762</td>
<td>0.924</td>
</tr>
<tr>
<td>J6</td>
<td>1.009</td>
<td>1.010</td>
<td>1.007</td>
<td>1.007</td>
<td>1.008</td>
<td>1.010</td>
<td>1.015</td>
<td>0.991</td>
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<td>J7</td>
<td>1.000</td>
<td>1.030</td>
<td>0.924</td>
<td>0.922</td>
<td>0.904</td>
<td>0.916</td>
<td>1.171</td>
<td>0.462</td>
</tr>
<tr>
<td>J8</td>
<td>0.911</td>
<td>0.915</td>
<td>0.840</td>
<td>0.848</td>
<td>0.844</td>
<td>0.817</td>
<td>1.061</td>
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</tr>
<tr>
<td>J9</td>
<td>0.000</td>
<td>0.688</td>
<td>0.466</td>
<td>0.481</td>
<td>0.474</td>
<td>0.391</td>
<td>0.999</td>
<td>0.000</td>
</tr>
<tr>
<td>J10</td>
<td>0.000</td>
<td>0.581</td>
<td>0.401</td>
<td>0.440</td>
<td>0.401</td>
<td>0.363</td>
<td>0.999</td>
<td>0.000</td>
</tr>
</tbody>
</table>

NF: no forgetting allowed  
FI: fixed inputs  
NSC: no sliding controller
Figure A.4: Coyote earthquake: a) time series (unscaled); and b) maximum inter-story displacements of the top 10 floors under various control strategies.

Table A.5: Performance indices, Coyote Earthquake, simulation 4.

<table>
<thead>
<tr>
<th>index</th>
<th>visc.</th>
<th>LQR</th>
<th>SOI</th>
<th>NF</th>
<th>FI</th>
<th>NSC</th>
<th>ON</th>
<th>OFF</th>
</tr>
</thead>
<tbody>
<tr>
<td>J1</td>
<td>0.735</td>
<td>0.827</td>
<td>0.631</td>
<td>0.664</td>
<td>0.627</td>
<td>0.640</td>
<td>0.949</td>
<td>0.960</td>
</tr>
<tr>
<td>J2</td>
<td>0.686</td>
<td>0.967</td>
<td>0.638</td>
<td>0.658</td>
<td>0.690</td>
<td>0.690</td>
<td>1.027</td>
<td>0.945</td>
</tr>
<tr>
<td>J3</td>
<td>0.938</td>
<td>0.940</td>
<td>0.942</td>
<td>0.943</td>
<td>0.940</td>
<td>0.945</td>
<td>0.941</td>
<td>0.941</td>
</tr>
<tr>
<td>J4</td>
<td>0.993</td>
<td>0.958</td>
<td>0.972</td>
<td>0.977</td>
<td>0.979</td>
<td>0.970</td>
<td>1.027</td>
<td>0.986</td>
</tr>
<tr>
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<td>1.022</td>
<td>1.107</td>
<td>1.068</td>
<td>1.066</td>
<td>1.070</td>
<td>1.069</td>
<td>1.108</td>
<td>0.990</td>
</tr>
<tr>
<td>J6</td>
<td>0.999</td>
<td>0.984</td>
<td>0.986</td>
<td>0.987</td>
<td>0.985</td>
<td>0.987</td>
<td>0.985</td>
<td>0.987</td>
</tr>
<tr>
<td>J7</td>
<td>0.163</td>
<td>0.741</td>
<td>0.630</td>
<td>0.660</td>
<td>0.588</td>
<td>0.657</td>
<td>0.761</td>
<td>0.038</td>
</tr>
<tr>
<td>J8</td>
<td>0.118</td>
<td>0.491</td>
<td>0.461</td>
<td>0.476</td>
<td>0.471</td>
<td>0.500</td>
<td>0.490</td>
<td>0.025</td>
</tr>
<tr>
<td>J9</td>
<td>0.000</td>
<td>0.609</td>
<td>0.907</td>
<td>0.898</td>
<td>0.898</td>
<td>0.889</td>
<td>0.999</td>
<td>0.000</td>
</tr>
<tr>
<td>J10</td>
<td>0.000</td>
<td>0.511</td>
<td>0.768</td>
<td>0.785</td>
<td>0.825</td>
<td>0.816</td>
<td>0.999</td>
<td>0.000</td>
</tr>
</tbody>
</table>

NF: no forgetting allowed
FI: fixed inputs
NSC: no sliding controller
A.5 Denali 2002

Figure A.5: Denali earthquake: a) time series (unscaled); and b) maximum inter-story displacements of the top 10 floors under various control strategies.

Table A.6: Performance indices, Denali Earthquake, simulation 4.

<table>
<thead>
<tr>
<th>index</th>
<th>visc.</th>
<th>LQR</th>
<th>SOI</th>
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<th>FI</th>
<th>NSC</th>
<th>ON</th>
<th>OFF</th>
</tr>
</thead>
<tbody>
<tr>
<td>J1</td>
<td>0.712</td>
<td>0.738</td>
<td>0.799</td>
<td>0.793</td>
<td>0.803</td>
<td>0.826</td>
<td>0.683</td>
<td>0.919</td>
</tr>
<tr>
<td>J2</td>
<td>0.870</td>
<td>0.926</td>
<td>0.941</td>
<td>0.941</td>
<td>0.945</td>
<td>0.965</td>
<td>0.856</td>
<td>0.978</td>
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<tr>
<td>J3</td>
<td>0.721</td>
<td>0.740</td>
<td>0.783</td>
<td>0.778</td>
<td>0.795</td>
<td>0.833</td>
<td>0.659</td>
<td>0.942</td>
</tr>
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<td>J4</td>
<td>0.878</td>
<td>0.936</td>
<td>0.938</td>
<td>0.959</td>
<td>0.938</td>
<td>0.951</td>
<td>0.884</td>
<td>0.966</td>
</tr>
<tr>
<td>J5</td>
<td>0.799</td>
<td>0.803</td>
<td>0.876</td>
<td>0.870</td>
<td>0.870</td>
<td>0.906</td>
<td>0.760</td>
<td>0.922</td>
</tr>
<tr>
<td>J6</td>
<td>0.908</td>
<td>0.964</td>
<td>0.933</td>
<td>0.932</td>
<td>0.940</td>
<td>0.945</td>
<td>0.982</td>
<td>0.988</td>
</tr>
<tr>
<td>J7</td>
<td>1.000</td>
<td>1.129</td>
<td>0.988</td>
<td>0.990</td>
<td>0.975</td>
<td>0.908</td>
<td>1.164</td>
<td>0.446</td>
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<tr>
<td>J8</td>
<td>0.911</td>
<td>1.052</td>
<td>0.941</td>
<td>0.943</td>
<td>0.916</td>
<td>0.873</td>
<td>1.108</td>
<td>0.354</td>
</tr>
<tr>
<td>J9</td>
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<td>0.755</td>
<td>0.472</td>
<td>0.461</td>
<td>0.463</td>
<td>0.376</td>
<td>1.000</td>
<td>0.000</td>
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<tr>
<td>J10</td>
<td>0.000</td>
<td>0.680</td>
<td>0.434</td>
<td>0.432</td>
<td>0.421</td>
<td>0.349</td>
<td>1.000</td>
<td>0.000</td>
</tr>
</tbody>
</table>

NF: no forgetting allowed
FI: fixed inputs
NSC: no sliding controller
APPENDIX A. SUPPLEMENTAL EARTHQUAKE SIMULATION RESULTS

A.6 Dinar 1985

Figure A.6: Dinar earthquake: a) time series (unscaled); and b) maximum inter-story displacements of the top 10 floors under various control strategies.

Table A.7: Performance indices, Dinar Earthquake, simulation 4.

<table>
<thead>
<tr>
<th>index</th>
<th>visc.</th>
<th>LQR</th>
<th>SOI</th>
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<th>FI</th>
<th>NSC</th>
<th>ON</th>
<th>OFF</th>
</tr>
</thead>
<tbody>
<tr>
<td>J1</td>
<td>0.570</td>
<td>0.564</td>
<td>0.625</td>
<td>0.613</td>
<td>0.612</td>
<td>0.654</td>
<td>0.524</td>
<td>0.742</td>
</tr>
<tr>
<td>J2</td>
<td>0.528</td>
<td>0.510</td>
<td>0.580</td>
<td>0.577</td>
<td>0.581</td>
<td>0.595</td>
<td>0.534</td>
<td>0.645</td>
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<tr>
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<td>0.622</td>
<td>0.580</td>
<td>0.630</td>
<td>0.608</td>
<td>0.604</td>
<td>0.674</td>
<td>0.568</td>
<td>0.769</td>
</tr>
<tr>
<td>J4</td>
<td>0.839</td>
<td>0.852</td>
<td>0.785</td>
<td>0.821</td>
<td>0.820</td>
<td>0.816</td>
<td>0.834</td>
<td>0.823</td>
</tr>
<tr>
<td>J5</td>
<td>0.537</td>
<td>0.487</td>
<td>0.555</td>
<td>0.547</td>
<td>0.544</td>
<td>0.581</td>
<td>0.540</td>
<td>0.656</td>
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<tr>
<td>J6</td>
<td>0.996</td>
<td>0.905</td>
<td>0.900</td>
<td>0.900</td>
<td>0.899</td>
<td>0.901</td>
<td>0.907</td>
<td>0.890</td>
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<tr>
<td>J7</td>
<td>0.896</td>
<td>0.962</td>
<td>0.940</td>
<td>0.952</td>
<td>0.960</td>
<td>0.906</td>
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<tr>
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<td>0.780</td>
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<td>0.904</td>
<td>0.863</td>
<td>0.988</td>
<td>0.171</td>
</tr>
<tr>
<td>J9</td>
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<td>0.748</td>
<td>0.476</td>
<td>0.503</td>
<td>0.476</td>
<td>0.425</td>
<td>0.999</td>
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<tr>
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<td>0.422</td>
<td>0.425</td>
<td>0.425</td>
<td>0.388</td>
<td>0.999</td>
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</tbody>
</table>

NF: no forgetting allowed
FI: fixed inputs
NSC: no sliding controller
A.7 Duzce 1999

Figure A.7: Duzce earthquake: a) time series (unscaled); and b) maximum inter-story displacements of the top 10 floors under various control strategies.

Table A.8: Performance indices, Duzce Earthquake, simulation 4.

<table>
<thead>
<tr>
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<th>FI</th>
<th>NSC</th>
<th>ON</th>
<th>OFF</th>
</tr>
</thead>
<tbody>
<tr>
<td>J1</td>
<td>0.668</td>
<td>0.632</td>
<td>0.661</td>
<td>0.652</td>
<td>0.686</td>
<td>0.659</td>
<td>0.563</td>
<td>0.922</td>
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<td>J2</td>
<td>0.755</td>
<td>0.721</td>
<td>0.725</td>
<td>0.741</td>
<td>0.758</td>
<td>0.749</td>
<td>0.711</td>
<td>0.945</td>
</tr>
<tr>
<td>J3</td>
<td>0.938</td>
<td>0.809</td>
<td>0.843</td>
<td>0.882</td>
<td>0.834</td>
<td>0.860</td>
<td>0.805</td>
<td>1.014</td>
</tr>
<tr>
<td>J4</td>
<td>0.918</td>
<td>0.967</td>
<td>0.969</td>
<td>0.959</td>
<td>0.951</td>
<td>0.952</td>
<td>0.962</td>
<td>0.970</td>
</tr>
<tr>
<td>J5</td>
<td>0.803</td>
<td>0.753</td>
<td>0.818</td>
<td>0.808</td>
<td>0.839</td>
<td>0.807</td>
<td>0.717</td>
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</tr>
<tr>
<td>J6</td>
<td>0.996</td>
<td>1.012</td>
<td>1.000</td>
<td>0.999</td>
<td>0.997</td>
<td>0.999</td>
<td>1.017</td>
<td>0.994</td>
</tr>
<tr>
<td>J7</td>
<td>0.659</td>
<td>0.894</td>
<td>0.934</td>
<td>0.941</td>
<td>0.952</td>
<td>0.923</td>
<td>0.969</td>
<td>0.153</td>
</tr>
<tr>
<td>J8</td>
<td>0.537</td>
<td>0.813</td>
<td>0.883</td>
<td>0.879</td>
<td>0.872</td>
<td>0.887</td>
<td>0.960</td>
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<tr>
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<td>0.000</td>
<td>0.703</td>
<td>0.633</td>
<td>0.590</td>
<td>0.550</td>
<td>0.556</td>
<td>0.999</td>
<td>0.000</td>
</tr>
<tr>
<td>J10</td>
<td>0.000</td>
<td>0.582</td>
<td>0.502</td>
<td>0.486</td>
<td>0.484</td>
<td>0.437</td>
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<td>0.000</td>
</tr>
</tbody>
</table>

NF: no forgetting allowed
FI: fixed inputs
NSC: no sliding controller
APPENDIX A. SUPPLEMENTAL EARTHQUAKE SIMULATION RESULTS

A.8 Erzican 1992

![Graphs showing earthquake simulation results]

Figure A.8: Erzican earthquake: a) time series (unscaled); and b) maximum inter-story displacements of the top 10 floors under various control strategies.

Table A.9: Performance indices, Erzican Earthquake, simulation 4.

<table>
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<tr>
<th>index</th>
<th>visc.</th>
<th>LQR</th>
<th>SOI</th>
<th>NF</th>
<th>FI</th>
<th>NSC</th>
<th>ON</th>
<th>OFF</th>
</tr>
</thead>
<tbody>
<tr>
<td>J1</td>
<td>0.687</td>
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<td>0.692</td>
<td>0.695</td>
<td>0.680</td>
<td>0.710</td>
<td>0.726</td>
<td>0.935</td>
</tr>
<tr>
<td>J2</td>
<td>0.818</td>
<td>0.789</td>
<td>0.858</td>
<td>0.851</td>
<td>0.841</td>
<td>0.908</td>
<td>0.794</td>
<td>0.972</td>
</tr>
<tr>
<td>J3</td>
<td>0.749</td>
<td>0.750</td>
<td>0.817</td>
<td>0.813</td>
<td>0.796</td>
<td>0.805</td>
<td>0.736</td>
<td>0.950</td>
</tr>
<tr>
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<td>0.950</td>
<td>0.953</td>
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<td>1.032</td>
<td>1.022</td>
<td>1.008</td>
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<td>0.991</td>
</tr>
<tr>
<td>J5</td>
<td>0.831</td>
<td>0.818</td>
<td>0.871</td>
<td>0.884</td>
<td>0.845</td>
<td>0.879</td>
<td>0.882</td>
<td>0.960</td>
</tr>
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<tr>
<td>J8</td>
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<td>0.628</td>
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<td>0.631</td>
<td>0.485</td>
<td>0.999</td>
<td>0.000</td>
</tr>
<tr>
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<td>0.624</td>
<td>0.541</td>
<td>0.544</td>
<td>0.541</td>
<td>0.416</td>
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</tr>
</tbody>
</table>

NF: no forgetting allowed
FI: fixed inputs
NSC: no sliding controller

256
A.9 Friuli 1976

(a) [Graph showing time series (unscaled) for Friuli earthquake]

(b) [Graph showing maximum inter-story displacements of the top 10 floors under various control strategies]

Figure A.9: Friuli earthquake: a) time series (unscaled); and b) maximum inter-story displacements of the top 10 floors under various control strategies.

Table A.10: Performance indices, Friuli Earthquake, simulation 4.

<table>
<thead>
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<th>OFF</th>
</tr>
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<td>J1</td>
<td>0.675</td>
<td>0.614</td>
<td>0.487</td>
<td>0.454</td>
<td>0.544</td>
<td>0.511</td>
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<td>0.810</td>
<td>0.590</td>
<td>0.613</td>
<td>0.716</td>
<td>0.568</td>
<td>0.841</td>
<td>0.922</td>
</tr>
<tr>
<td>J3</td>
<td>0.964</td>
<td>0.968</td>
<td>0.965</td>
<td>0.959</td>
<td>1.004</td>
<td>0.965</td>
<td>0.967</td>
<td>0.984</td>
</tr>
<tr>
<td>J4</td>
<td>0.964</td>
<td>0.968</td>
<td>0.965</td>
<td>0.959</td>
<td>1.004</td>
<td>0.965</td>
<td>0.967</td>
<td>0.984</td>
</tr>
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<td>0.992</td>
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<tr>
<td>J6</td>
<td>0.999</td>
<td>0.991</td>
<td>0.992</td>
<td>0.992</td>
<td>0.992</td>
<td>0.992</td>
<td>0.991</td>
<td>0.989</td>
</tr>
<tr>
<td>J7</td>
<td>0.260</td>
<td>0.945</td>
<td>0.914</td>
<td>0.913</td>
<td>0.946</td>
<td>0.930</td>
<td>0.976</td>
<td>0.075</td>
</tr>
<tr>
<td>J8</td>
<td>0.229</td>
<td>0.920</td>
<td>0.846</td>
<td>0.811</td>
<td>0.873</td>
<td>0.840</td>
<td>0.964</td>
<td>0.050</td>
</tr>
<tr>
<td>J9</td>
<td>0.000</td>
<td>0.739</td>
<td>0.788</td>
<td>0.628</td>
<td>0.663</td>
<td>0.764</td>
<td>0.999</td>
<td>0.000</td>
</tr>
<tr>
<td>J10</td>
<td>0.000</td>
<td>0.629</td>
<td>0.553</td>
<td>0.516</td>
<td>0.568</td>
<td>0.576</td>
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</tr>
</tbody>
</table>

NF: no forgetting allowed
FI: fixed inputs
NSC: no sliding controller
APPENDIX A. SUPPLEMENTAL EARTHQUAKE SIMULATION RESULTS

A.10 Gilroy 2002

![Image of time series and displacement graphs]

Figure A.10: Gilroy earthquake: a) time series (unscaled); and b) maximum inter-story displacements of the top 10 floors under various control strategies.

Table A.11: Performance indices, Gilroy Earthquake, simulation 4.

<table>
<thead>
<tr>
<th>index</th>
<th>visc.</th>
<th>LQR</th>
<th>SOI</th>
<th>NF</th>
<th>FI</th>
<th>NSC</th>
<th>ON</th>
<th>OFF</th>
</tr>
</thead>
<tbody>
<tr>
<td>J1</td>
<td>0.776</td>
<td>0.820</td>
<td>0.849</td>
<td>0.870</td>
<td>0.868</td>
<td>0.883</td>
<td>0.807</td>
<td>0.963</td>
</tr>
<tr>
<td>J2</td>
<td>0.799</td>
<td>0.840</td>
<td>0.859</td>
<td>0.862</td>
<td>0.869</td>
<td>0.876</td>
<td>0.815</td>
<td>0.961</td>
</tr>
<tr>
<td>J3</td>
<td>0.765</td>
<td>0.879</td>
<td>0.851</td>
<td>0.876</td>
<td>0.886</td>
<td>0.900</td>
<td>0.878</td>
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</tr>
<tr>
<td>J4</td>
<td>0.820</td>
<td>0.893</td>
<td>0.881</td>
<td>0.879</td>
<td>0.880</td>
<td>0.877</td>
<td>0.884</td>
<td>0.949</td>
</tr>
<tr>
<td>J5</td>
<td>0.813</td>
<td>0.804</td>
<td>0.863</td>
<td>0.869</td>
<td>0.858</td>
<td>0.871</td>
<td>0.804</td>
<td>0.950</td>
</tr>
<tr>
<td>J6</td>
<td>1.028</td>
<td>1.032</td>
<td>1.017</td>
<td>1.018</td>
<td>1.018</td>
<td>1.024</td>
<td>1.025</td>
<td>1.010</td>
</tr>
<tr>
<td>J7</td>
<td>1.000</td>
<td>1.049</td>
<td>0.962</td>
<td>0.979</td>
<td>0.969</td>
<td>0.936</td>
<td>1.095</td>
<td>0.326</td>
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<tr>
<td>J8</td>
<td>0.902</td>
<td>0.981</td>
<td>0.937</td>
<td>0.941</td>
<td>0.940</td>
<td>0.918</td>
<td>1.045</td>
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<tr>
<td>J9</td>
<td>0.000</td>
<td>0.728</td>
<td>0.595</td>
<td>0.581</td>
<td>0.635</td>
<td>0.441</td>
<td>1.000</td>
<td>0.000</td>
</tr>
<tr>
<td>J10</td>
<td>0.000</td>
<td>0.560</td>
<td>0.425</td>
<td>0.429</td>
<td>0.447</td>
<td>0.344</td>
<td>1.000</td>
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NF: no forgetting allowed
FI: fixed inputs
NSC: no sliding controller
Figure A.11: Imperial Valley earthquake: a) time series (unscaled); and b) maximum inter-story displacements of the top 10 floors under various control strategies.

Table A.12: Performance indices, Imperial Valley Earthquake, simulation 4.

<table>
<thead>
<tr>
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<th>FI</th>
<th>NSC</th>
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<th>OFF</th>
</tr>
</thead>
<tbody>
<tr>
<td>J1</td>
<td>0.722</td>
<td>0.617</td>
<td>0.697</td>
<td>0.744</td>
<td>0.735</td>
<td>0.735</td>
<td>0.718</td>
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<tr>
<td>J2</td>
<td>0.676</td>
<td>0.606</td>
<td>0.717</td>
<td>0.733</td>
<td>0.748</td>
<td>0.741</td>
<td>0.654</td>
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<tr>
<td>J3</td>
<td>0.964</td>
<td>0.930</td>
<td>0.940</td>
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<td>0.943</td>
<td>0.939</td>
<td>0.933</td>
<td>0.955</td>
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<tr>
<td>J4</td>
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<td>0.883</td>
<td>0.917</td>
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<td>0.939</td>
<td>0.933</td>
<td>0.864</td>
<td>0.952</td>
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<td>0.895</td>
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<td>0.971</td>
<td>1.008</td>
<td>1.014</td>
<td>0.976</td>
<td>0.955</td>
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<td>0.962</td>
<td>0.962</td>
<td>0.966</td>
<td>0.966</td>
<td>0.958</td>
</tr>
<tr>
<td>J7</td>
<td>0.613</td>
<td>0.854</td>
<td>0.891</td>
<td>0.898</td>
<td>0.881</td>
<td>0.877</td>
<td>0.975</td>
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<td>0.813</td>
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<td>0.107</td>
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<td>0.000</td>
<td>0.651</td>
<td>0.526</td>
<td>0.503</td>
<td>0.504</td>
<td>0.493</td>
<td>0.999</td>
<td>0.000</td>
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<tr>
<td>J10</td>
<td>0.000</td>
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<td>0.441</td>
<td>0.439</td>
<td>0.449</td>
<td>0.999</td>
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</tbody>
</table>

NF: no forgetting allowed
FI: fixed inputs
NSC: no sliding controller
APPENDIX A. SUPPLEMENTAL EARTHQUAKE SIMULATION RESULTS

A.12 Irpinia 1980

Figure A.12: Irpinia earthquake: a) time series (unscaled); and b) maximum inter-story displacements of the top 10 floors under various control strategies.

Table A.13: Performance indices, Irpinia Earthquake, simulation 4.

<table>
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<th>FI</th>
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<th>OFF</th>
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<td>0.542</td>
<td>0.800</td>
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<tr>
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<td>0.572</td>
<td>0.624</td>
<td>0.669</td>
<td>0.529</td>
<td>0.644</td>
<td>0.752</td>
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<td>0.635</td>
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<td>0.595</td>
<td>0.857</td>
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<td>0.581</td>
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<td>0.710</td>
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<td>0.587</td>
<td>0.574</td>
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<td>0.560</td>
<td>0.890</td>
<td>0.951</td>
<td>0.545</td>
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<td>0.690</td>
<td>0.691</td>
<td>0.980</td>
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<td>0.775</td>
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<td>0.054</td>
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<tr>
<td>J8</td>
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<td>0.642</td>
<td>0.588</td>
<td>0.623</td>
<td>0.665</td>
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<td>0.000</td>
<td>0.557</td>
<td>0.578</td>
<td>0.545</td>
<td>0.562</td>
<td>0.480</td>
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<tr>
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<td>0.505</td>
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<td>0.514</td>
<td>0.538</td>
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NF: no forgetting allowed
FI: fixed inputs
NSC: no sliding controller
A.13 Kern County 1952

Figure A.13: Kern earthquake: a) time series (unscaled); and b) maximum inter-story displacements of the top 10 floors under various control strategies.

Table A.14: Performance indices, Kern Earthquake, simulation 4.

<table>
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<th>FI</th>
<th>NSC</th>
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<th>OFF</th>
</tr>
</thead>
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<td>0.734</td>
<td>0.697</td>
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<td>0.932</td>
</tr>
<tr>
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<td>0.733</td>
<td>0.653</td>
<td>0.651</td>
<td>0.668</td>
<td>0.631</td>
<td>0.652</td>
<td>0.990</td>
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<tr>
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<td>0.932</td>
<td>0.963</td>
<td>0.963</td>
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<td>0.795</td>
<td>0.923</td>
<td>0.967</td>
</tr>
<tr>
<td>J6</td>
<td>0.979</td>
<td>0.959</td>
<td>0.961</td>
<td>0.962</td>
<td>0.968</td>
<td>0.965</td>
<td>0.933</td>
<td>0.984</td>
</tr>
<tr>
<td>J7</td>
<td>0.714</td>
<td>0.937</td>
<td>0.963</td>
<td>0.962</td>
<td>0.963</td>
<td>0.923</td>
<td>0.984</td>
<td>0.133</td>
</tr>
<tr>
<td>J8</td>
<td>0.553</td>
<td>0.888</td>
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<td>0.919</td>
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<td>0.000</td>
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<td>0.625</td>
<td>0.564</td>
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</tr>
<tr>
<td>J10</td>
<td>0.000</td>
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<td>0.504</td>
<td>0.531</td>
<td>0.484</td>
<td>0.432</td>
<td>0.999</td>
<td>0.000</td>
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</tbody>
</table>

NF: no forgetting allowed
FI: fixed inputs
NSC: no sliding controller
APPENDIX A. SUPPLEMENTAL EARTHQUAKE SIMULATION RESULTS

A.14 Kobe 1995

Figure A.14: Kobe earthquake: a) time series (unscaled); and b) maximum inter-story displacements of the top 10 floors under various control strategies.

Table A.15: Performance indices, Kobe Earthquake, simulation 4.

<table>
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<th>FI</th>
<th>NSC</th>
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<th>OFF</th>
</tr>
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<tbody>
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<td>0.539</td>
<td>0.549</td>
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<td>0.715</td>
<td>0.683</td>
<td>0.658</td>
<td>0.823</td>
<td>0.933</td>
</tr>
<tr>
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<td>0.992</td>
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<td>1.002</td>
<td>0.998</td>
<td>1.022</td>
<td>1.028</td>
<td>1.029</td>
<td>0.995</td>
</tr>
<tr>
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<td>1.002</td>
<td>0.998</td>
<td>1.022</td>
<td>1.028</td>
<td>1.029</td>
<td>0.995</td>
</tr>
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<td>0.992</td>
<td>1.020</td>
<td>0.989</td>
<td>1.063</td>
<td>0.963</td>
</tr>
<tr>
<td>J6</td>
<td>0.995</td>
<td>0.988</td>
<td>0.991</td>
<td>0.991</td>
<td>0.991</td>
<td>0.992</td>
<td>0.988</td>
<td>0.992</td>
</tr>
<tr>
<td>J7</td>
<td>0.512</td>
<td>0.874</td>
<td>0.879</td>
<td>0.923</td>
<td>0.912</td>
<td>0.942</td>
<td>0.974</td>
<td>0.098</td>
</tr>
<tr>
<td>J8</td>
<td>0.340</td>
<td>0.818</td>
<td>0.840</td>
<td>0.848</td>
<td>0.851</td>
<td>0.838</td>
<td>0.962</td>
<td>0.071</td>
</tr>
<tr>
<td>J9</td>
<td>0.000</td>
<td>0.671</td>
<td>0.549</td>
<td>0.500</td>
<td>0.494</td>
<td>0.480</td>
<td>0.999</td>
<td>0.000</td>
</tr>
<tr>
<td>J10</td>
<td>0.000</td>
<td>0.612</td>
<td>0.476</td>
<td>0.439</td>
<td>0.446</td>
<td>0.409</td>
<td>0.999</td>
<td>0.000</td>
</tr>
</tbody>
</table>

NF: no forgetting allowed
FI: fixed inputs
NSC: no sliding controller
A.15 Kocaeli 1999

Figure A.15: Kocaeli earthquake: a) time series (unscaled); and b) maximum inter-story displacements of the top 10 floors under various control strategies.

Table A.16: Performance indices, Kocaeli Earthquake, simulation 4.

<table>
<thead>
<tr>
<th>index</th>
<th>visc.</th>
<th>LQR</th>
<th>SOI</th>
<th>NF</th>
<th>FI</th>
<th>NSC</th>
<th>ON</th>
<th>OFF</th>
</tr>
</thead>
<tbody>
<tr>
<td>J1</td>
<td>0.676</td>
<td>0.706</td>
<td>0.776</td>
<td>0.789</td>
<td>0.758</td>
<td>0.817</td>
<td>0.705</td>
<td>0.948</td>
</tr>
<tr>
<td>J2</td>
<td>0.729</td>
<td>0.629</td>
<td>0.724</td>
<td>0.697</td>
<td>0.698</td>
<td>0.765</td>
<td>0.601</td>
<td>0.935</td>
</tr>
<tr>
<td>J3</td>
<td>0.968</td>
<td>1.029</td>
<td>1.058</td>
<td>1.064</td>
<td>1.066</td>
<td>1.050</td>
<td>0.920</td>
<td>0.983</td>
</tr>
<tr>
<td>J4</td>
<td>1.000</td>
<td>1.069</td>
<td>1.100</td>
<td>1.106</td>
<td>1.108</td>
<td>1.091</td>
<td>0.940</td>
<td>1.006</td>
</tr>
<tr>
<td>J5</td>
<td>0.779</td>
<td>0.874</td>
<td>0.816</td>
<td>0.806</td>
<td>0.846</td>
<td>0.831</td>
<td>0.820</td>
<td>0.946</td>
</tr>
<tr>
<td>J6</td>
<td>0.999</td>
<td>1.013</td>
<td>0.999</td>
<td>1.001</td>
<td>1.004</td>
<td>1.000</td>
<td>1.009</td>
<td>0.998</td>
</tr>
<tr>
<td>J7</td>
<td>0.814</td>
<td>1.007</td>
<td>0.993</td>
<td>1.017</td>
<td>0.999</td>
<td>0.956</td>
<td>1.011</td>
<td>0.190</td>
</tr>
<tr>
<td>J8</td>
<td>0.615</td>
<td>0.977</td>
<td>0.942</td>
<td>0.944</td>
<td>0.938</td>
<td>0.915</td>
<td>0.996</td>
<td>0.145</td>
</tr>
<tr>
<td>J9</td>
<td>0.000</td>
<td>0.754</td>
<td>0.749</td>
<td>0.773</td>
<td>0.811</td>
<td>0.667</td>
<td>1.000</td>
<td>0.000</td>
</tr>
<tr>
<td>J10</td>
<td>0.000</td>
<td>0.649</td>
<td>0.673</td>
<td>0.670</td>
<td>0.725</td>
<td>0.590</td>
<td>1.000</td>
<td>0.000</td>
</tr>
</tbody>
</table>

NF: no forgetting allowed
FI: fixed inputs
NSC: no sliding controller
APPENDIX A. SUPPLEMENTAL EARTHQUAKE SIMULATION RESULTS

A.16 Loma Prieta 1989

Figure A.16: Loma Prieta earthquake: a) time series (unscaled); and b) maximum inter-story displacements of the top 10 floors under various control strategies.

Table A.17: Performance indices, Loma Prieta Earthquake, simulation 4.

<table>
<thead>
<tr>
<th>index</th>
<th>visc.</th>
<th>LQR</th>
<th>SOI</th>
<th>NF</th>
<th>FI</th>
<th>NSC</th>
<th>ON</th>
<th>OFF</th>
</tr>
</thead>
<tbody>
<tr>
<td>J1</td>
<td>0.621</td>
<td>0.598</td>
<td>0.689</td>
<td>0.692</td>
<td>0.712</td>
<td>0.704</td>
<td>0.608</td>
<td>0.895</td>
</tr>
<tr>
<td>J2</td>
<td>0.660</td>
<td>0.678</td>
<td>0.747</td>
<td>0.722</td>
<td>0.777</td>
<td>0.755</td>
<td>0.810</td>
<td>0.875</td>
</tr>
<tr>
<td>J3</td>
<td>0.781</td>
<td>0.880</td>
<td>0.872</td>
<td>0.896</td>
<td>0.909</td>
<td>0.832</td>
<td>0.865</td>
<td>0.881</td>
</tr>
<tr>
<td>J4</td>
<td>0.932</td>
<td>1.050</td>
<td>1.041</td>
<td>1.069</td>
<td>1.085</td>
<td>0.993</td>
<td>1.033</td>
<td>0.982</td>
</tr>
<tr>
<td>J5</td>
<td>0.903</td>
<td>0.947</td>
<td>0.947</td>
<td>0.943</td>
<td>0.931</td>
<td>0.946</td>
<td>1.003</td>
<td>0.930</td>
</tr>
<tr>
<td>J6</td>
<td>1.012</td>
<td>1.045</td>
<td>1.023</td>
<td>1.022</td>
<td>1.021</td>
<td>1.024</td>
<td>1.049</td>
<td>0.998</td>
</tr>
<tr>
<td>J7</td>
<td>0.817</td>
<td>0.940</td>
<td>0.907</td>
<td>0.890</td>
<td>0.893</td>
<td>0.880</td>
<td>0.967</td>
<td>0.189</td>
</tr>
<tr>
<td>J8</td>
<td>0.715</td>
<td>0.888</td>
<td>0.842</td>
<td>0.849</td>
<td>0.824</td>
<td>0.813</td>
<td>0.958</td>
<td>0.139</td>
</tr>
<tr>
<td>J9</td>
<td>0.000</td>
<td>0.684</td>
<td>0.766</td>
<td>0.776</td>
<td>0.776</td>
<td>0.692</td>
<td>1.000</td>
<td>0.000</td>
</tr>
<tr>
<td>J10</td>
<td>0.000</td>
<td>0.583</td>
<td>0.664</td>
<td>0.656</td>
<td>0.668</td>
<td>0.518</td>
<td>1.000</td>
<td>0.000</td>
</tr>
</tbody>
</table>

NF: no forgetting allowed
FI: fixed inputs
NSC: no sliding controller

264
A.17 Mammoth Lakes 1980

Figure A.17: Mammoth Lakes earthquake: a) time series (unscaled); and b) maximum inter-story displacements of the top 10 floors under various control strategies.

Table A.18: Performance indices, Mammoth Lakes Earthquake, simulation 4.

<table>
<thead>
<tr>
<th>index</th>
<th>visc.</th>
<th>LQR</th>
<th>SOI</th>
<th>NF</th>
<th>FI</th>
<th>NSC</th>
<th>ON</th>
<th>OFF</th>
</tr>
</thead>
<tbody>
<tr>
<td>J1</td>
<td>0.568</td>
<td>0.965</td>
<td>0.689</td>
<td>0.688</td>
<td>0.683</td>
<td>0.642</td>
<td>1.074</td>
<td>0.898</td>
</tr>
<tr>
<td>J2</td>
<td>0.666</td>
<td>1.303</td>
<td>0.873</td>
<td>0.928</td>
<td>0.857</td>
<td>0.835</td>
<td>1.472</td>
<td>0.854</td>
</tr>
<tr>
<td>J3</td>
<td>0.985</td>
<td>0.973</td>
<td>0.963</td>
<td>0.961</td>
<td>0.960</td>
<td>0.969</td>
<td>0.965</td>
<td>0.988</td>
</tr>
<tr>
<td>J4</td>
<td>0.985</td>
<td>0.973</td>
<td>0.963</td>
<td>0.961</td>
<td>0.960</td>
<td>0.969</td>
<td>0.965</td>
<td>0.988</td>
</tr>
<tr>
<td>J5</td>
<td>1.040</td>
<td>1.105</td>
<td>1.081</td>
<td>1.081</td>
<td>1.080</td>
<td>1.071</td>
<td>1.120</td>
<td>0.998</td>
</tr>
<tr>
<td>J6</td>
<td>0.998</td>
<td>0.983</td>
<td>0.986</td>
<td>0.985</td>
<td>0.985</td>
<td>0.985</td>
<td>0.983</td>
<td>0.987</td>
</tr>
<tr>
<td>J7</td>
<td>0.196</td>
<td>0.612</td>
<td>0.505</td>
<td>0.570</td>
<td>0.521</td>
<td>0.653</td>
<td>0.615</td>
<td>0.033</td>
</tr>
<tr>
<td>J8</td>
<td>0.118</td>
<td>0.410</td>
<td>0.443</td>
<td>0.460</td>
<td>0.437</td>
<td>0.471</td>
<td>0.425</td>
<td>0.027</td>
</tr>
<tr>
<td>J9</td>
<td>0.000</td>
<td>0.651</td>
<td>0.899</td>
<td>0.894</td>
<td>0.950</td>
<td>0.856</td>
<td>0.999</td>
<td>0.000</td>
</tr>
<tr>
<td>J10</td>
<td>0.000</td>
<td>0.568</td>
<td>0.785</td>
<td>0.769</td>
<td>0.892</td>
<td>0.726</td>
<td>0.999</td>
<td>0.000</td>
</tr>
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</table>

NF: no forgetting allowed
FI: fixed inputs
NSC: no sliding controller
Appendix A. Supplemental Earthquake Simulation Results

A.18 Manjil 1990

Figure A.18: Manjil earthquake: a) time series (unscaled); and b) maximum inter-story displacements of the top 10 floors under various control strategies.

Table A.19: Performance indices, Manjil Earthquake, simulation 4.

<table>
<thead>
<tr>
<th>index</th>
<th>visc.</th>
<th>LQR</th>
<th>SOI</th>
<th>NF</th>
<th>FI</th>
<th>NSC</th>
<th>ON</th>
<th>OFF</th>
</tr>
</thead>
<tbody>
<tr>
<td>J1</td>
<td>0.671</td>
<td>0.482</td>
<td>0.583</td>
<td>0.598</td>
<td>0.592</td>
<td>0.618</td>
<td>0.476</td>
<td>0.938</td>
</tr>
<tr>
<td>J2</td>
<td>0.666</td>
<td>0.536</td>
<td>0.635</td>
<td>0.639</td>
<td>0.655</td>
<td>0.647</td>
<td>0.569</td>
<td>0.936</td>
</tr>
<tr>
<td>J3</td>
<td>0.993</td>
<td>1.023</td>
<td>0.993</td>
<td>1.007</td>
<td>0.998</td>
<td>1.000</td>
<td>1.024</td>
<td>0.976</td>
</tr>
<tr>
<td>J4</td>
<td>0.944</td>
<td>0.958</td>
<td>0.968</td>
<td>1.007</td>
<td>0.946</td>
<td>1.004</td>
<td>0.976</td>
<td>0.976</td>
</tr>
<tr>
<td>J5</td>
<td>0.856</td>
<td>0.827</td>
<td>0.852</td>
<td>0.872</td>
<td>0.861</td>
<td>0.848</td>
<td>0.836</td>
<td>0.998</td>
</tr>
<tr>
<td>J6</td>
<td>0.998</td>
<td>0.994</td>
<td>0.993</td>
<td>0.996</td>
<td>0.990</td>
<td>0.990</td>
<td>0.992</td>
<td>0.994</td>
</tr>
<tr>
<td>J7</td>
<td>0.626</td>
<td>0.884</td>
<td>0.958</td>
<td>0.927</td>
<td>0.961</td>
<td>0.943</td>
<td>0.973</td>
<td>0.191</td>
</tr>
<tr>
<td>J8</td>
<td>0.490</td>
<td>0.801</td>
<td>0.886</td>
<td>0.864</td>
<td>0.905</td>
<td>0.877</td>
<td>0.966</td>
<td>0.108</td>
</tr>
<tr>
<td>J9</td>
<td>0.000</td>
<td>0.629</td>
<td>0.625</td>
<td>0.634</td>
<td>0.672</td>
<td>0.525</td>
<td>1.000</td>
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</tr>
<tr>
<td>J10</td>
<td>0.000</td>
<td>0.545</td>
<td>0.476</td>
<td>0.476</td>
<td>0.503</td>
<td>0.409</td>
<td>1.000</td>
<td>0.000</td>
</tr>
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</table>

NF: no forgetting allowed
FI: fixed inputs
NSC: no sliding controller
Figure A.19: Michoacan earthquake: a) time series (unscaled); and b) maximum inter-story displacements of the top 10 floors under various control strategies.

Table A.20: Performance indices, Michoacan Earthquake, simulation 4.

<table>
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<th>NF</th>
<th>FI</th>
<th>NSC</th>
<th>ON</th>
<th>OFF</th>
</tr>
</thead>
<tbody>
<tr>
<td>J1</td>
<td>0.906</td>
<td>0.919</td>
<td>0.964</td>
<td>0.964</td>
<td>0.968</td>
<td>0.967</td>
<td>0.888</td>
<td>0.977</td>
</tr>
<tr>
<td>J2</td>
<td>0.940</td>
<td>0.949</td>
<td>0.983</td>
<td>0.983</td>
<td>0.984</td>
<td>0.984</td>
<td>0.931</td>
<td>0.981</td>
</tr>
<tr>
<td>J3</td>
<td>0.891</td>
<td>0.906</td>
<td>0.959</td>
<td>0.959</td>
<td>0.961</td>
<td>0.964</td>
<td>0.886</td>
<td>0.975</td>
</tr>
<tr>
<td>J4</td>
<td>0.945</td>
<td>0.951</td>
<td>0.975</td>
<td>0.975</td>
<td>0.976</td>
<td>0.975</td>
<td>0.961</td>
<td>0.982</td>
</tr>
<tr>
<td>J5</td>
<td>0.911</td>
<td>0.930</td>
<td>0.957</td>
<td>0.957</td>
<td>0.957</td>
<td>0.957</td>
<td>0.909</td>
<td>0.964</td>
</tr>
<tr>
<td>J6</td>
<td>0.963</td>
<td>0.964</td>
<td>0.989</td>
<td>0.989</td>
<td>0.990</td>
<td>0.990</td>
<td>0.943</td>
<td>0.992</td>
</tr>
<tr>
<td>J7</td>
<td>1.000</td>
<td>1.438</td>
<td>1.146</td>
<td>1.146</td>
<td>1.029</td>
<td>1.064</td>
<td>1.643</td>
<td>0.882</td>
</tr>
<tr>
<td>J8</td>
<td>0.911</td>
<td>1.045</td>
<td>0.777</td>
<td>0.777</td>
<td>0.771</td>
<td>0.766</td>
<td>1.233</td>
<td>0.431</td>
</tr>
<tr>
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<td>0.000</td>
<td>0.718</td>
<td>0.453</td>
<td>0.453</td>
<td>0.442</td>
<td>0.445</td>
<td>1.000</td>
<td>0.000</td>
</tr>
<tr>
<td>J10</td>
<td>0.000</td>
<td>0.655</td>
<td>0.434</td>
<td>0.434</td>
<td>0.421</td>
<td>0.402</td>
<td>1.000</td>
<td>0.000</td>
</tr>
</tbody>
</table>

NF: no forgetting allowed
FI: fixed inputs
NSC: no sliding controller
Figure A.20: Nahanni earthquake: a) time series (unscaled); and b) maximum inter-story displacements of the top 10 floors under various control strategies.

Table A.21: Performance indices, Nahanni Earthquake, simulation 4.

<table>
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<th>NF</th>
<th>FI</th>
<th>NSC</th>
<th>ON</th>
<th>OFF</th>
</tr>
</thead>
<tbody>
<tr>
<td>J1</td>
<td>0.759</td>
<td>0.693</td>
<td>0.674</td>
<td>0.684</td>
<td>0.716</td>
<td>0.675</td>
<td>1.044</td>
<td>0.961</td>
</tr>
<tr>
<td>J2</td>
<td>0.662</td>
<td>0.884</td>
<td>0.603</td>
<td>0.635</td>
<td>0.667</td>
<td>0.626</td>
<td>1.014</td>
<td>0.944</td>
</tr>
<tr>
<td>J3</td>
<td>0.990</td>
<td>0.936</td>
<td>0.947</td>
<td>0.943</td>
<td>0.943</td>
<td>0.943</td>
<td>0.941</td>
<td>0.962</td>
</tr>
<tr>
<td>J4</td>
<td>0.996</td>
<td>0.940</td>
<td>0.940</td>
<td>0.943</td>
<td>0.943</td>
<td>0.933</td>
<td>0.941</td>
<td>0.967</td>
</tr>
<tr>
<td>J5</td>
<td>1.011</td>
<td>0.992</td>
<td>0.980</td>
<td>0.980</td>
<td>0.980</td>
<td>0.971</td>
<td>0.992</td>
<td>0.957</td>
</tr>
<tr>
<td>J6</td>
<td>0.998</td>
<td>0.957</td>
<td>0.956</td>
<td>0.955</td>
<td>0.956</td>
<td>0.956</td>
<td>0.958</td>
<td>0.955</td>
</tr>
<tr>
<td>J7</td>
<td>0.280</td>
<td>0.838</td>
<td>0.795</td>
<td>0.719</td>
<td>0.870</td>
<td>0.758</td>
<td>0.965</td>
<td>0.055</td>
</tr>
<tr>
<td>J8</td>
<td>0.195</td>
<td>0.724</td>
<td>0.601</td>
<td>0.596</td>
<td>0.599</td>
<td>0.571</td>
<td>0.832</td>
<td>0.040</td>
</tr>
<tr>
<td>J9</td>
<td>0.000</td>
<td>0.610</td>
<td>0.809</td>
<td>0.815</td>
<td>0.863</td>
<td>0.771</td>
<td>0.999</td>
<td>0.000</td>
</tr>
<tr>
<td>J10</td>
<td>0.000</td>
<td>0.539</td>
<td>0.660</td>
<td>0.652</td>
<td>0.777</td>
<td>0.664</td>
<td>0.999</td>
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</tr>
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</table>

NF: no forgetting allowed  
FI: fixed inputs  
NSC: no sliding controller
Figure A.21: New Zealand earthquake: a) time series (unscaled); and b) maximum inter-story displacements of the top 10 floors under various control strategies.

Table A.22: Performance indices, New Zealand Earthquake, simulation 4.

<table>
<thead>
<tr>
<th>index</th>
<th>visc.</th>
<th>LQR</th>
<th>SOI</th>
<th>NF</th>
<th>FI</th>
<th>NSC</th>
<th>ON</th>
<th>OFF</th>
</tr>
</thead>
<tbody>
<tr>
<td>J1</td>
<td>0.571</td>
<td>0.658</td>
<td>0.619</td>
<td>0.604</td>
<td>0.652</td>
<td>0.684</td>
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<tr>
<td>J2</td>
<td>0.658</td>
<td>0.822</td>
<td>0.798</td>
<td>0.789</td>
<td>0.835</td>
<td>0.876</td>
<td>1.148</td>
<td>0.933</td>
</tr>
<tr>
<td>J3</td>
<td>0.984</td>
<td>0.945</td>
<td>0.952</td>
<td>0.949</td>
<td>0.945</td>
<td>0.948</td>
<td>0.944</td>
<td>0.968</td>
</tr>
<tr>
<td>J4</td>
<td>1.019</td>
<td>0.962</td>
<td>0.973</td>
<td>0.969</td>
<td>0.974</td>
<td>0.984</td>
<td>0.958</td>
<td>0.999</td>
</tr>
<tr>
<td>J5</td>
<td>0.987</td>
<td>0.990</td>
<td>0.984</td>
<td>0.986</td>
<td>0.987</td>
<td>0.968</td>
<td>0.979</td>
<td>0.964</td>
</tr>
<tr>
<td>J6</td>
<td>0.992</td>
<td>0.968</td>
<td>0.970</td>
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<td>0.969</td>
<td>0.970</td>
<td>0.967</td>
<td>0.972</td>
</tr>
<tr>
<td>J7</td>
<td>0.331</td>
<td>0.505</td>
<td>0.472</td>
<td>0.513</td>
<td>0.513</td>
<td>0.463</td>
<td>0.963</td>
<td>0.059</td>
</tr>
<tr>
<td>J8</td>
<td>0.208</td>
<td>0.451</td>
<td>0.373</td>
<td>0.388</td>
<td>0.421</td>
<td>0.399</td>
<td>0.824</td>
<td>0.045</td>
</tr>
<tr>
<td>J9</td>
<td>0.000</td>
<td>0.420</td>
<td>0.497</td>
<td>0.407</td>
<td>0.501</td>
<td>0.378</td>
<td>0.998</td>
<td>0.000</td>
</tr>
<tr>
<td>J10</td>
<td>0.000</td>
<td>0.393</td>
<td>0.289</td>
<td>0.292</td>
<td>0.338</td>
<td>0.261</td>
<td>0.998</td>
<td>0.000</td>
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NF: no forgetting allowed
FI: fixed inputs
NSC: no sliding controller
Figure A.22: Norcia earthquake: a) time series (unscaled); and b) maximum inter-story displacements of the top 10 floors under various control strategies.

Table A.23: Performance indices, Norcia Earthquake, simulation 4.

<table>
<thead>
<tr>
<th></th>
<th>visc.</th>
<th>LQR</th>
<th>SOI</th>
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<th>FI</th>
<th>NSC</th>
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<th>OFF</th>
</tr>
</thead>
<tbody>
<tr>
<td>J1</td>
<td>0.508</td>
<td>0.834</td>
<td>0.668</td>
<td>0.628</td>
<td>0.648</td>
<td>0.685</td>
<td>1.038</td>
<td>0.878</td>
</tr>
<tr>
<td>J2</td>
<td>0.472</td>
<td>0.973</td>
<td>0.814</td>
<td>0.782</td>
<td>0.889</td>
<td>0.724</td>
<td>1.197</td>
<td>0.782</td>
</tr>
<tr>
<td>J3</td>
<td>1.020</td>
<td>0.970</td>
<td>0.996</td>
<td>1.000</td>
<td>1.069</td>
<td>1.033</td>
<td>0.965</td>
<td>1.002</td>
</tr>
<tr>
<td>J4</td>
<td>1.020</td>
<td>0.970</td>
<td>0.996</td>
<td>1.000</td>
<td>1.069</td>
<td>1.033</td>
<td>0.965</td>
<td>1.002</td>
</tr>
<tr>
<td>J5</td>
<td>1.014</td>
<td>1.002</td>
<td>0.998</td>
<td>0.996</td>
<td>0.999</td>
<td>0.997</td>
<td>1.002</td>
<td>0.961</td>
</tr>
<tr>
<td>J6</td>
<td>0.994</td>
<td>0.955</td>
<td>0.954</td>
<td>0.955</td>
<td>0.954</td>
<td>0.955</td>
<td>0.955</td>
<td>0.954</td>
</tr>
<tr>
<td>J7</td>
<td>0.328</td>
<td>0.599</td>
<td>0.677</td>
<td>0.682</td>
<td>0.654</td>
<td>0.592</td>
<td>0.862</td>
<td>0.052</td>
</tr>
<tr>
<td>J8</td>
<td>0.193</td>
<td>0.464</td>
<td>0.512</td>
<td>0.505</td>
<td>0.486</td>
<td>0.474</td>
<td>0.661</td>
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<tr>
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<td>0.000</td>
<td>0.494</td>
<td>0.454</td>
<td>0.369</td>
<td>0.430</td>
<td>0.397</td>
<td>0.999</td>
<td>0.000</td>
</tr>
<tr>
<td>J10</td>
<td>0.000</td>
<td>0.413</td>
<td>0.281</td>
<td>0.273</td>
<td>0.283</td>
<td>0.258</td>
<td>0.999</td>
<td>0.000</td>
</tr>
</tbody>
</table>

NF: no forgetting allowed
FI: fixed inputs
NSC: no sliding controller
A.23 Northridge 1994

Figure A.23: Northridge earthquake: a) time series (unscaled); and b) maximum inter-story displacements of the top 10 floors under various control strategies.

Table A.24: Performance indices, Northridge Earthquake, simulation 4.

<table>
<thead>
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<th>index</th>
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<th>FI</th>
<th>NSC</th>
<th>ON</th>
<th>OFF</th>
</tr>
</thead>
<tbody>
<tr>
<td>J1</td>
<td>0.064</td>
<td>0.053</td>
<td>0.045</td>
<td>0.048</td>
<td>0.044</td>
<td>0.047</td>
<td>0.063</td>
<td>0.093</td>
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<tr>
<td>J2</td>
<td>0.070</td>
<td>0.054</td>
<td>0.058</td>
<td>0.058</td>
<td>0.056</td>
<td>0.057</td>
<td>0.066</td>
<td>0.085</td>
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<tr>
<td>J3</td>
<td>0.267</td>
<td>0.260</td>
<td>0.260</td>
<td>0.260</td>
<td>0.260</td>
<td>0.260</td>
<td>0.260</td>
<td>0.255</td>
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<tr>
<td>J4</td>
<td>0.343</td>
<td>0.326</td>
<td>0.326</td>
<td>0.326</td>
<td>0.326</td>
<td>0.327</td>
<td>0.327</td>
<td>0.337</td>
</tr>
<tr>
<td>J5</td>
<td>0.220</td>
<td>0.221</td>
<td>0.222</td>
<td>0.222</td>
<td>0.222</td>
<td>0.222</td>
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</tr>
<tr>
<td>J6</td>
<td>0.822</td>
<td>0.778</td>
<td>0.779</td>
<td>0.779</td>
<td>0.779</td>
<td>0.779</td>
<td>0.778</td>
<td>0.781</td>
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<tr>
<td>J7</td>
<td>0.321</td>
<td>0.630</td>
<td>0.667</td>
<td>0.678</td>
<td>0.662</td>
<td>0.642</td>
<td>0.965</td>
<td>0.089</td>
</tr>
<tr>
<td>J8</td>
<td>0.236</td>
<td>0.586</td>
<td>0.552</td>
<td>0.569</td>
<td>0.580</td>
<td>0.561</td>
<td>0.905</td>
<td>0.047</td>
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<tr>
<td>J9</td>
<td>0.000</td>
<td>0.557</td>
<td>0.456</td>
<td>0.445</td>
<td>0.451</td>
<td>0.434</td>
<td>0.999</td>
<td>0.000</td>
</tr>
<tr>
<td>J10</td>
<td>0.000</td>
<td>0.510</td>
<td>0.407</td>
<td>0.402</td>
<td>0.421</td>
<td>0.372</td>
<td>0.999</td>
<td>0.000</td>
</tr>
</tbody>
</table>

NF: no forgetting allowed
FI: fixed inputs
NSC: no sliding controller
APPENDIX A. SUPPLEMENTAL EARTHQUAKE SIMULATION RESULTS

A.24 Parkfield 1966

Figure A.24: Parkfield earthquake: a) time series (unscaled); and b) maximum inter-story displacements of the top 10 floors under various control strategies.

Table A.25: Performance indices, Parkfield Earthquake, simulation 4.

<table>
<thead>
<tr>
<th>index</th>
<th>visc.</th>
<th>LQR</th>
<th>SOI</th>
<th>NF</th>
<th>FI</th>
<th>NSC</th>
<th>ON</th>
<th>OFF</th>
</tr>
</thead>
<tbody>
<tr>
<td>J1</td>
<td>0.676</td>
<td>0.776</td>
<td>0.809</td>
<td>0.747</td>
<td>0.795</td>
<td>0.774</td>
<td>1.123</td>
<td>0.944</td>
</tr>
<tr>
<td>J2</td>
<td>0.693</td>
<td>0.766</td>
<td>0.610</td>
<td>0.650</td>
<td>0.616</td>
<td>0.644</td>
<td>0.932</td>
<td>0.940</td>
</tr>
<tr>
<td>J3</td>
<td>0.983</td>
<td>0.994</td>
<td>0.958</td>
<td>0.969</td>
<td>0.978</td>
<td>0.978</td>
<td>0.982</td>
<td>0.986</td>
</tr>
<tr>
<td>J4</td>
<td>1.002</td>
<td>0.989</td>
<td>0.987</td>
<td>0.982</td>
<td>0.966</td>
<td>0.974</td>
<td>1.009</td>
<td>0.997</td>
</tr>
<tr>
<td>J5</td>
<td>0.987</td>
<td>1.060</td>
<td>1.030</td>
<td>1.026</td>
<td>1.017</td>
<td>1.028</td>
<td>1.059</td>
<td>0.983</td>
</tr>
<tr>
<td>J6</td>
<td>0.993</td>
<td>0.974</td>
<td>0.977</td>
<td>0.979</td>
<td>0.978</td>
<td>0.979</td>
<td>0.970</td>
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<tr>
<td>J7</td>
<td>0.343</td>
<td>0.673</td>
<td>0.915</td>
<td>0.879</td>
<td>0.882</td>
<td>0.936</td>
<td>0.957</td>
<td>0.063</td>
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<tr>
<td>J8</td>
<td>0.221</td>
<td>0.593</td>
<td>0.705</td>
<td>0.725</td>
<td>0.657</td>
<td>0.722</td>
<td>0.902</td>
<td>0.048</td>
</tr>
<tr>
<td>J9</td>
<td>0.000</td>
<td>0.527</td>
<td>0.713</td>
<td>0.755</td>
<td>0.729</td>
<td>0.717</td>
<td>0.999</td>
<td>0.000</td>
</tr>
<tr>
<td>J10</td>
<td>0.000</td>
<td>0.445</td>
<td>0.374</td>
<td>0.392</td>
<td>0.355</td>
<td>0.363</td>
<td>0.999</td>
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</table>

NF: no forgetting allowed
FI: fixed inputs
NSC: no sliding controller
A.25 San Fernando 1971

Figure A.25: San Fernando earthquake: a) time series (unscaled); and b) maximum inter-story displacements of the top 10 floors under various control strategies.

Table A.26: Performance indices, San Fernando Earthquake, simulation 4.

<table>
<thead>
<tr>
<th>index</th>
<th>visc.</th>
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<th>SOI</th>
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<th>FI</th>
<th>NSC</th>
<th>ON</th>
<th>OFF</th>
</tr>
</thead>
<tbody>
<tr>
<td>J1</td>
<td>0.655</td>
<td>0.572</td>
<td>0.683</td>
<td>0.683</td>
<td>0.708</td>
<td>0.674</td>
<td>0.636</td>
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<td>J2</td>
<td>0.753</td>
<td>0.802</td>
<td>0.797</td>
<td>0.797</td>
<td>0.822</td>
<td>0.774</td>
<td>0.870</td>
<td>0.951</td>
</tr>
<tr>
<td>J3</td>
<td>0.821</td>
<td>0.781</td>
<td>0.784</td>
<td>0.770</td>
<td>0.785</td>
<td>0.787</td>
<td>0.735</td>
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</tr>
<tr>
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<td>0.914</td>
<td>0.810</td>
<td>0.826</td>
<td>0.823</td>
<td>0.857</td>
<td>0.855</td>
<td>0.794</td>
<td>0.960</td>
</tr>
<tr>
<td>J5</td>
<td>0.930</td>
<td>0.915</td>
<td>0.932</td>
<td>0.934</td>
<td>0.940</td>
<td>0.954</td>
<td>0.933</td>
<td>0.963</td>
</tr>
<tr>
<td>J6</td>
<td>0.969</td>
<td>0.906</td>
<td>0.918</td>
<td>0.918</td>
<td>0.920</td>
<td>0.918</td>
<td>0.885</td>
<td>0.955</td>
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<tr>
<td>J7</td>
<td>0.468</td>
<td>0.912</td>
<td>0.939</td>
<td>0.938</td>
<td>0.934</td>
<td>0.940</td>
<td>0.973</td>
<td>0.105</td>
</tr>
<tr>
<td>J8</td>
<td>0.421</td>
<td>0.855</td>
<td>0.852</td>
<td>0.863</td>
<td>0.878</td>
<td>0.845</td>
<td>0.963</td>
<td>0.075</td>
</tr>
<tr>
<td>J9</td>
<td>0.000</td>
<td>0.782</td>
<td>0.675</td>
<td>0.614</td>
<td>0.607</td>
<td>0.559</td>
<td>0.999</td>
<td>0.000</td>
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<tr>
<td>J10</td>
<td>0.000</td>
<td>0.696</td>
<td>0.495</td>
<td>0.485</td>
<td>0.524</td>
<td>0.458</td>
<td>0.999</td>
<td>0.000</td>
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</tbody>
</table>

NF: no forgetting allowed
FI: fixed inputs
NSC: no sliding controller
Figure A.26: San Francisco earthquake: a) time series (unscaled); and b) maximum inter-story displacements of the top 10 floors under various control strategies.

Table A.27: Performance indices, San Francisco Earthquake, simulation 4.

<table>
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<th>SOI</th>
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<th>FI</th>
<th>NSC</th>
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<th>OFF</th>
</tr>
</thead>
<tbody>
<tr>
<td>J1</td>
<td>0.962</td>
<td>0.973</td>
<td>0.959</td>
<td>0.959</td>
<td>0.958</td>
<td>0.965</td>
<td>1.028</td>
<td>0.951</td>
</tr>
<tr>
<td>J2</td>
<td>0.827</td>
<td>1.293</td>
<td>0.972</td>
<td>0.988</td>
<td>1.005</td>
<td>0.946</td>
<td>1.405</td>
<td>0.852</td>
</tr>
<tr>
<td>J3</td>
<td>1.005</td>
<td>1.004</td>
<td>1.004</td>
<td>1.004</td>
<td>1.004</td>
<td>1.005</td>
<td>1.002</td>
<td>0.994</td>
</tr>
<tr>
<td>J4</td>
<td>0.951</td>
<td>0.974</td>
<td>0.964</td>
<td>0.964</td>
<td>0.964</td>
<td>0.967</td>
<td>0.978</td>
<td>0.978</td>
</tr>
<tr>
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<td>1.000</td>
<td>0.991</td>
<td>0.991</td>
<td>0.991</td>
<td>0.991</td>
<td>0.990</td>
<td>0.991</td>
<td>0.990</td>
</tr>
<tr>
<td>J6</td>
<td>0.998</td>
<td>0.988</td>
<td>0.988</td>
<td>0.988</td>
<td>0.988</td>
<td>0.988</td>
<td>0.987</td>
<td>0.988</td>
</tr>
<tr>
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<td>0.426</td>
<td>0.452</td>
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<td>0.446</td>
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<td>0.339</td>
<td>0.348</td>
<td>0.329</td>
<td>0.341</td>
<td>0.261</td>
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</tr>
<tr>
<td>J9</td>
<td>0.000</td>
<td>0.675</td>
<td>0.946</td>
<td>0.952</td>
<td>0.962</td>
<td>0.939</td>
<td>1.000</td>
<td>0.000</td>
</tr>
<tr>
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<td>0.000</td>
<td>0.582</td>
<td>0.843</td>
<td>0.864</td>
<td>0.905</td>
<td>0.805</td>
<td>1.000</td>
<td>0.000</td>
</tr>
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</table>

NF: no forgetting allowed
FI: fixed inputs
NSC: no sliding controller
A.27 San Salvador 1986

Figure A.27: San Salvador earthquake: a) time series (unscaled); and b) maximum inter-story displacements of the top 10 floors under various control strategies.

Table A.28: Performance indices, San Salvador Earthquake, simulation 4.

<table>
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<th>SOI</th>
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<th>FI</th>
<th>NSC</th>
<th>ON</th>
<th>OFF</th>
</tr>
</thead>
<tbody>
<tr>
<td>J1</td>
<td>0.663</td>
<td>0.622</td>
<td>0.679</td>
<td>0.666</td>
<td>0.702</td>
<td>0.679</td>
<td>0.635</td>
<td>0.925</td>
</tr>
<tr>
<td>J2</td>
<td>0.694</td>
<td>0.679</td>
<td>0.750</td>
<td>0.727</td>
<td>0.765</td>
<td>0.753</td>
<td>0.669</td>
<td>0.934</td>
</tr>
<tr>
<td>J3</td>
<td>0.657</td>
<td>0.679</td>
<td>0.698</td>
<td>0.698</td>
<td>0.703</td>
<td>0.693</td>
<td>0.672</td>
<td>0.858</td>
</tr>
<tr>
<td>J4</td>
<td>0.944</td>
<td>0.975</td>
<td>1.003</td>
<td>1.002</td>
<td>1.010</td>
<td>0.995</td>
<td>0.966</td>
<td>0.989</td>
</tr>
<tr>
<td>J5</td>
<td>0.859</td>
<td>0.856</td>
<td>0.858</td>
<td>0.859</td>
<td>0.859</td>
<td>0.857</td>
<td>0.918</td>
<td>0.936</td>
</tr>
<tr>
<td>J6</td>
<td>0.998</td>
<td>1.007</td>
<td>1.000</td>
<td>1.000</td>
<td>0.999</td>
<td>0.997</td>
<td>1.007</td>
<td>0.996</td>
</tr>
<tr>
<td>J7</td>
<td>0.960</td>
<td>0.982</td>
<td>0.920</td>
<td>0.995</td>
<td>0.987</td>
<td>0.917</td>
<td>0.987</td>
<td>0.244</td>
</tr>
<tr>
<td>J8</td>
<td>0.833</td>
<td>0.916</td>
<td>0.874</td>
<td>0.888</td>
<td>0.876</td>
<td>0.852</td>
<td>0.971</td>
<td>0.169</td>
</tr>
<tr>
<td>J9</td>
<td>0.000</td>
<td>0.629</td>
<td>0.728</td>
<td>0.757</td>
<td>0.734</td>
<td>0.688</td>
<td>0.999</td>
<td>0.000</td>
</tr>
<tr>
<td>J10</td>
<td>0.000</td>
<td>0.561</td>
<td>0.596</td>
<td>0.643</td>
<td>0.646</td>
<td>0.571</td>
<td>0.999</td>
<td>0.000</td>
</tr>
</tbody>
</table>

NF: no forgetting allowed
FI: fixed inputs
NSC: no sliding controller
Figure A.28: Spitak earthquake: a) time series (unscaled); and b) maximum inter-story displacements of the top 10 floors under various control strategies.

Table A.29: Performance indices, Spitak Earthquake, simulation 4.

<table>
<thead>
<tr>
<th>index</th>
<th>visc.</th>
<th>LQR</th>
<th>SOI</th>
<th>NF</th>
<th>FI</th>
<th>NSC</th>
<th>ON</th>
<th>OFF</th>
</tr>
</thead>
<tbody>
<tr>
<td>J1</td>
<td>0.746</td>
<td>0.794</td>
<td>0.744</td>
<td>0.766</td>
<td>0.755</td>
<td>0.757</td>
<td>0.771</td>
<td>0.962</td>
</tr>
<tr>
<td>J2</td>
<td>0.800</td>
<td>0.836</td>
<td>0.810</td>
<td>0.822</td>
<td>0.843</td>
<td>0.834</td>
<td>0.812</td>
<td>0.966</td>
</tr>
<tr>
<td>J3</td>
<td>0.842</td>
<td>0.878</td>
<td>0.897</td>
<td>0.905</td>
<td>0.923</td>
<td>0.909</td>
<td>0.856</td>
<td>0.927</td>
</tr>
<tr>
<td>J4</td>
<td>0.940</td>
<td>0.980</td>
<td>1.001</td>
<td>1.010</td>
<td>1.029</td>
<td>1.014</td>
<td>0.955</td>
<td>0.987</td>
</tr>
<tr>
<td>J5</td>
<td>0.964</td>
<td>0.950</td>
<td>0.933</td>
<td>0.957</td>
<td>0.966</td>
<td>0.976</td>
<td>0.948</td>
<td>0.967</td>
</tr>
<tr>
<td>J6</td>
<td>1.005</td>
<td>1.017</td>
<td>1.014</td>
<td>1.014</td>
<td>1.013</td>
<td>1.005</td>
<td>1.023</td>
<td>0.987</td>
</tr>
<tr>
<td>J7</td>
<td>0.657</td>
<td>0.918</td>
<td>0.937</td>
<td>0.939</td>
<td>0.912</td>
<td>0.860</td>
<td>0.969</td>
<td>0.164</td>
</tr>
<tr>
<td>J8</td>
<td>0.606</td>
<td>0.857</td>
<td>0.851</td>
<td>0.868</td>
<td>0.816</td>
<td>0.791</td>
<td>0.963</td>
<td>0.112</td>
</tr>
<tr>
<td>J9</td>
<td>0.000</td>
<td>0.661</td>
<td>0.534</td>
<td>0.582</td>
<td>0.538</td>
<td>0.463</td>
<td>0.999</td>
<td>0.000</td>
</tr>
<tr>
<td>J10</td>
<td>0.000</td>
<td>0.567</td>
<td>0.465</td>
<td>0.465</td>
<td>0.466</td>
<td>0.408</td>
<td>0.999</td>
<td>0.000</td>
</tr>
</tbody>
</table>

NF: no forgetting allowed
FI: fixed inputs
NSC: no sliding controller
Figure A.29: Tabas earthquake: a) time series (unscaled); and b) maximum inter-story displacements of the top 10 floors under various control strategies.

Table A.30: Performance indices, Tabas Earthquake, simulation 4.

<table>
<thead>
<tr>
<th>index</th>
<th>visc.</th>
<th>LQR</th>
<th>SOI</th>
<th>NF</th>
<th>FI</th>
<th>NSC</th>
<th>ON</th>
<th>OFF</th>
</tr>
</thead>
<tbody>
<tr>
<td>J1</td>
<td>0.800</td>
<td>0.797</td>
<td>0.865</td>
<td>0.847</td>
<td>0.835</td>
<td>0.840</td>
<td>0.688</td>
<td>0.981</td>
</tr>
<tr>
<td>J2</td>
<td>0.716</td>
<td>0.739</td>
<td>0.773</td>
<td>0.775</td>
<td>0.761</td>
<td>0.776</td>
<td>0.666</td>
<td>0.946</td>
</tr>
<tr>
<td>J3</td>
<td>0.840</td>
<td>0.852</td>
<td>0.859</td>
<td>0.865</td>
<td>0.850</td>
<td>0.858</td>
<td>1.049</td>
<td>0.932</td>
</tr>
<tr>
<td>J4</td>
<td>0.952</td>
<td>0.912</td>
<td>0.899</td>
<td>0.907</td>
<td>0.928</td>
<td>0.924</td>
<td>0.963</td>
<td>0.964</td>
</tr>
<tr>
<td>J5</td>
<td>0.778</td>
<td>0.838</td>
<td>0.838</td>
<td>0.826</td>
<td>0.841</td>
<td>0.825</td>
<td>0.801</td>
<td>0.952</td>
</tr>
<tr>
<td>J6</td>
<td>0.981</td>
<td>0.946</td>
<td>0.947</td>
<td>0.945</td>
<td>0.949</td>
<td>0.949</td>
<td>0.946</td>
<td>0.963</td>
</tr>
<tr>
<td>J7</td>
<td>0.583</td>
<td>0.806</td>
<td>0.706</td>
<td>0.738</td>
<td>0.754</td>
<td>0.572</td>
<td>0.979</td>
<td>0.188</td>
</tr>
<tr>
<td>J8</td>
<td>0.487</td>
<td>0.698</td>
<td>0.628</td>
<td>0.628</td>
<td>0.651</td>
<td>0.473</td>
<td>0.967</td>
<td>0.112</td>
</tr>
<tr>
<td>J9</td>
<td>0.000</td>
<td>0.554</td>
<td>0.391</td>
<td>0.381</td>
<td>0.465</td>
<td>0.300</td>
<td>0.999</td>
<td>0.000</td>
</tr>
<tr>
<td>J10</td>
<td>0.000</td>
<td>0.489</td>
<td>0.346</td>
<td>0.356</td>
<td>0.382</td>
<td>0.270</td>
<td>0.999</td>
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</tr>
</tbody>
</table>

NF: no forgetting allowed
FI: fixed inputs
NSC: no sliding controller
Figure A.30: Victoria earthquake: a) time series (unscaled); and b) maximum inter-story displacements of the top 10 floors under various control strategies.

Table A.31: Performance indices, Victoria Earthquake, simulation 4.

<table>
<thead>
<tr>
<th>index</th>
<th>visc.</th>
<th>LQR</th>
<th>SOI</th>
<th>NF</th>
<th>FI</th>
<th>NSC</th>
<th>ON</th>
<th>OFF</th>
</tr>
</thead>
<tbody>
<tr>
<td>J1</td>
<td>0.581</td>
<td>0.600</td>
<td>0.627</td>
<td>0.630</td>
<td>0.599</td>
<td>0.584</td>
<td>0.902</td>
<td>0.900</td>
</tr>
<tr>
<td>J2</td>
<td>0.707</td>
<td>0.712</td>
<td>0.702</td>
<td>0.638</td>
<td>0.738</td>
<td>0.641</td>
<td>0.770</td>
<td>0.947</td>
</tr>
<tr>
<td>J3</td>
<td>0.977</td>
<td>0.949</td>
<td>0.913</td>
<td>0.957</td>
<td>0.937</td>
<td>0.911</td>
<td>0.908</td>
<td>0.912</td>
</tr>
<tr>
<td>J4</td>
<td>0.986</td>
<td>0.974</td>
<td>0.937</td>
<td>0.983</td>
<td>0.962</td>
<td>0.923</td>
<td>0.932</td>
<td>0.917</td>
</tr>
<tr>
<td>J5</td>
<td>1.050</td>
<td>0.971</td>
<td>1.017</td>
<td>0.996</td>
<td>1.028</td>
<td>0.973</td>
<td>1.007</td>
<td>0.945</td>
</tr>
<tr>
<td>J6</td>
<td>0.999</td>
<td>0.914</td>
<td>0.907</td>
<td>0.910</td>
<td>0.908</td>
<td>0.908</td>
<td>0.915</td>
<td>0.896</td>
</tr>
<tr>
<td>J7</td>
<td>0.422</td>
<td>0.791</td>
<td>0.947</td>
<td>0.933</td>
<td>0.930</td>
<td>0.903</td>
<td>0.970</td>
<td>0.080</td>
</tr>
<tr>
<td>J8</td>
<td>0.314</td>
<td>0.682</td>
<td>0.791</td>
<td>0.747</td>
<td>0.751</td>
<td>0.703</td>
<td>0.947</td>
<td>0.069</td>
</tr>
<tr>
<td>J9</td>
<td>0.000</td>
<td>0.614</td>
<td>0.632</td>
<td>0.637</td>
<td>0.649</td>
<td>0.589</td>
<td>0.999</td>
<td>0.000</td>
</tr>
<tr>
<td>J10</td>
<td>0.000</td>
<td>0.509</td>
<td>0.444</td>
<td>0.409</td>
<td>0.455</td>
<td>0.358</td>
<td>0.999</td>
<td>0.000</td>
</tr>
</tbody>
</table>

NF: no forgetting allowed  
FI: fixed inputs  
NSC: no sliding controller


280


[73] Ikeda, Y. Active and semi-active vibration control of buildings in Japan Practical applications and verification. *Structural Control and Health Monitoring* 16, 7-8 (2009), 703–723.


293


BIBLIOGRAPHY


