Optimal control of structural dampers

Shibabrat Naik, Nicholas Sharp, Shane Ross

Engineering Science and Mechanics, Virginia Tech

May 13, 2014

Naik, Sharp, Ross (ESM, VT)

Motivation

- High rise structures are susceptible to dynamic excitations like earthquakes and wind gusts.
- Typically active tuned mass dampers, semi-active TMD, and MR dampers are engineered for controlling response.
- Trajectory based control uses information from phase space and optimal sets to reach or move a solution subset.
- For our interests, objective is to reduce inhabitant discomfort by reducing excessive sway in top floors and adverse structural stresses.

Modeling challenges

• Efforts in structutal health monitoring has been focussed on controlling response under earthquake as base excitations.



- Damper characteristics are controlled based on the feedback from the structure to optimize cost function of very high dimensional (100 or so) state vector.
- Response to wind load is calculated from empirical gust formulae and designed using probabilistic approach towards worst gust over the life span of the structure.

Reduced order model



- Model the structure as a cantilever beam with simple oscillation
- Assumptions:
 - Oscillation only in first mode
 - No damping coefficient for structure
 - Apply wind force entirely at top floor
- This system has just **two** degrees of freedom
- Use an equivalent lumped mass, $m_L = \frac{33}{140}mL$ and $c_d = \alpha m_d + \beta k_d$

Equations of motion and state-space model

Mass-spring model with a damper: $\mathbf{M}\ddot{\vec{x}} + \mathbf{C}\dot{\vec{x}} + \mathbf{K}\vec{x} = \vec{F}$ with $\vec{x} = \begin{vmatrix} x \\ x_d \end{vmatrix}$

$$\mathbf{M} = \begin{bmatrix} m_L & 0\\ 0 & m_d \end{bmatrix}, \ \mathbf{C} = \begin{bmatrix} c_d & -c_d\\ -c_d & c_d \end{bmatrix}, \ \mathbf{K} = \begin{bmatrix} k+k_d & -k_d\\ -k_d & k_d \end{bmatrix}, \ \vec{F} = \begin{bmatrix} W(t)\\ 0 \end{bmatrix}$$

$$\dot{s} = \mathbf{A}s + \mathbf{B}w$$

 $z = \mathbf{P}s + \mathbf{Q}w$

$$\mathbf{P} = \begin{bmatrix} \mathbf{I}_{N \times N} & \mathbf{0}_{N \times N} \\ \mathbf{0}_{N \times N} & \mathbf{I}_{N \times N} \\ -\mathbf{M}^{-1}\mathbf{K} & -\mathbf{M}^{-1}\mathbf{C} \end{bmatrix}, \ \mathbf{Q} = \begin{bmatrix} \mathbf{0}_{N \times N} \\ \mathbf{0}_{N \times N} \\ -\mathbf{M}^{-1} \end{bmatrix}$$

Wind gust and related statistics

- Wind velocity is a **stochastic** variable which simulates physical wind effects
- Observations of wind speed follow a **gaussian** distribution
- Must consider **continuity** of wind, represented by the **autocorrelation**
- Simulate wind using **Markov chains** trained on experimental measurements



Time series of measured and synthetic wind speed [1]

Synthetic wind using Markov chains

- Constructing state transition matrix(or transition probability matrix, \mathbf{P}) for all the available wind states.
- Compute the cumulative probability $matrix(\mathbf{C})$ for the state transition matrix as: $C_{ij} = \sum_{k=1}^{j} P_{ik}$
- Initialize the state(s) with a random integer in $(1, N_s)$, where N_s is the number of wind states.
- The current state s corresponds to a row in \mathbf{C} and generate a random number R from the uniform random distribution over (0, 1)such that next state K is $C_{ik-1} \leq R \leq C_{ik}$.







7 / 15

Uncontrolled dynamic response

• Impulse and wind loading to test the validation of heavy mass



Displacement responses for impulse forcing at t=0 and wind loading for 30 mins. $m_d/m_L=1/10$

Uncontrolled dynamic response

• Wind loading with a light damper, indicating metric for objective function



Displacement responses for impulse forcing at t = 0 and wind loading for 30 mins. $m_d/m_L = 1/1000$ Naik, Sharp, Ross (ESM, VT) Control of dampers May 13, 2014 9 / 15

Optimal Control - Why is it hard?

• State includes wind

The wind must be included in the state because it affects future state probabilities

• Stochastic Wind is not a distribution Normal methods from stochastic optimal control do not apply

• Optimal trajectory only followed for one timestep Must take new wind information in to account and re-plan

Markov Decision Process

- This problem perfectly meets the definition of a Markov Decision Process (MDP):
 - System transitions from state to state according to a random input and user action
 - Each state has an associated cost
- These problems are studied in economics, robotics, and operations research
- There is not single method for finding solutions, but common techniques include **dynamic programming** and **reinforcement learning**

Dynamic Programming

- We design a dynamic programming algorithm to solve the problem
- Process the set of all possible states backwards from the horizon time T
- Appears to work, but $\mathcal{O}(N^5)$ complexity inhibits practical utility



A general example of overlapping substructure in dynamic programming (Wikimedia Commons)

Future approaches

- Investigate more techniques from literature on Markov Decision Processes
- Algorithms from machine learning could yield very good approximate solutions
- State space search on a weighted hypergraph, but might require a different cost metric



A hypergraph formulation of a similar problem (Courtesy of Oliver Junge)

Thanks to Dr. Singh, Dr. Bisht, Dr. Junge for their adviceQuestions?

F. Kaminsky, R. Kirchhoff, C. Syu, and J. Manwell, "A comparison of alternative approaches for the synthetic generation of a wind speed time series," *Journal of solar energy engineering*, vol. 113, no. 4, pp. 280–289, 1991.

U. Aldemir, "Optimal control of structures with semiactive-tuned mass dampers," *Journal of sound and vibration*, vol. 266, no. 4, pp. 847–874, 2003.

L. M. Jansen and S. J. Dyke, "Semiactive control strategies for mr dampers: comparative study," *Journal of Engineering Mechanics*, vol. 126, no. 8, pp. 795–803, 2000.

A. G. Davenport, "The application of statistical concepts to the wind loading of structures.," in *ICE Proceedings*, vol. 19, pp. 449–472, Thomas Telford, 1961.