Semi-active Vibration Damping Control of Wind Turbines using Q-Learning

Jimmy Zhang, Jingxiao Liu, Benson Zu

Re-introduce the Problem

We model a wind turbine tower using a single degree of freedom (SDOF) mass-spring-damper system and subject it to various wind profiles to observe the vibration characteristics under various loading and damping conditions. A model of a semi-active magnetorheological (MR) damper is used to induce changes in viscous damping for the system through adjusting voltage. Our goal is to develop an autonomous control policy to attenuate such vortex induced vibrations for the SDOF system by using Q-learning to deduce optimal damping ratios after obtaining some wind velocity reading.

Progress to Date

1. Data Collection

The experimental data comes from Weather Data Services at Halus Power Systems Wind turbine. The raw data consists of 965 hourly wind speed data recorded from 10/07/2021 to 11/08/2021.

2. Simulators

We modeled the velocity and displacement for a SDOF mass-spring-damper system using an assumed acceleration function following the Newmark's Beta implicit time integration scheme [1]. The inputs to this simulator are turbine characteristics such as mass, stiffness, diameter, height etc., and a force vector. The force vector is converted from wind velocity to an unit sinusoidal force vector by estimating the vorticity induced vibration frequencies for the given wind velocity and turbine profile [2].

The damping simulator mimics the behavior of a semi-active MR damper [3]. Through increasing voltage supplied to the MR damper, various levels of viscous damping for the system can be achieved. The effects of activating the MR damper can be determined through the velocity and displacement simulator above.

3. Q-Learning

We design a policy $\pi(s, a)$, where *s*, the states, are the total kinetic and potential energy stored within the vibration motion, and *a*, the actions, are different settings of voltage for the MR damping. Upon taking an action, the new total energy associated with the damped vibrations will be the new state, *s'*. The rewards associated with an action will be a function of (1) the ratio between *s'* and *s* and (2) the change in voltage. Positive rewards will be handed out for actions that lead to decreasing the energy, while negative rewards will be handed out for actions that lead to increasing the energy. Negative rewards will also be given out for actions that incur no change in energy, but are wasteful and increase voltage. The magnitude of the reward will scale with the ratio (1).

After generating a {*s, a, r, s'*} catalogue much like project two, the actions that generated the highest rewards will be chosen such that:

$$Q(s,a) \leftarrow Q(s,a) + \alpha \left(r + \gamma \max_{a'} Q(s', a') - Q(s,a) \right)$$
$$a = argmax_a Q(s,a)$$

Timeline to Completion

11/12 Simulation of inputs data including vibration energy extraction from wind/damping and rewards values
11/18 Establish reward values and train Q-learning model
11/22 Experimental testing and error analysis; fine-tuning hyperparameters: discount factor and learning rates.
11/28 Write up final paper while seeking peer and TA reviews

References

1. Chopra, A. K. (2020). Dynamics of structures: Theory and applications to earthquake engineering. Harlow: Pearson.

2. Fu, F. (2018). Design and Analysis of Complex Structures. Design and Analysis of Tall and Complex Structures, 5-80. doi:https://doi.org/10.1016/B978-0-08-101018-1.00002-2.

3. Spencer, B. F., Dyke, S. J., Sain, M. K., & Carlson, J. D. (1997). Phenomenological Model for Magnetorheological Dampers. Journal of Engineering Mechanics, 123(3), 230-238. doi:10.1061/(asce)0733-9399(1997)123:3(230)

Data

4. Data:https://www.visualcrossing.com/weather/weather-data-services#/viewData
   Location: 94679 Halus Power Systems Wind turbine builder in San Leandro, California