Robustness of multi-agent reinforcement learning control for a lockable-mass tuned mass damper

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Reinforcement learning (RL) is a class of machine learning methods aimed at solving control-like tasks [1]. Control is learned and applied by an agent that learns to select the best action through a series of interactions with the controlled system.

A potential application area of reinforcement learning is semi-active structural control. In such tasks, the optimal control signals are often unknown and cannot thus be used for training, as required by typical supervised learning techniques. The RL approach is more suitable, as it allows the control agent to progressively improve its decision-making strategy in a trial-and-error manner based on experiencing and received feedback (reward). This interaction-based approach also goes beyond typical unsupervised techniques, as it allows control signals to be actively tested rather than merely exploring pre-prepared datasets. Despite these advantages and remarkable achievements in other fields [2], reinforcement learning methods are still rarely applied in structural control, especially in semi-active control [3].

This contribution continues our earlier work on RL-based control of a seismically excited shear-type building [4], which examined the robustness of a typical single-agent RL controller. Here, the investigation is extended to multi-agent RL control, in which the ultimately applied control action is determined based on the recommendations of a group of independent RL agents. Control is applied via a tuned mass damper whose mass can be locked to or unlocked from the story in an on/off manner. The reward function used for agent training quantifies structural vibrations, and additionally, it includes a penalty term that promotes locking at moments of zero relative velocity, in order to avoid the associated impacts.

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