Application of Deep Reinforcement Learning in Semi-Active Control of Frame Structures Equipped with Multiple Damper Devices

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Abstract

In semi-active control of structures, control algorithms determine the adjustable reaction of dampers to mitigate the seismic response of the structure. Existing control algorithms typically follow a set of predefined rules. Alternatively, data-driven methods can learn from computer simulations to identify patterns and to make adaptive decisions. Deep reinforcement learning is a subset of machine learning that utilizes neural networks to perform optimal actions in dynamic environments. In this study, the seismic response of a 2D, 9-story frame structure equipped with multiple semi-active magnetorheological (MR) dampers was controlled using a Twin-Delayed Deep Deterministic Policy Gradient (TD3) reinforcement learning model that utilized a novel reward system. To assess the superiority of the method, the performance of the TD3 model was compared with that of the skyhook control algorithm.

Intelligent Damper Control

Magnetorheological (MR) dampers are the most widely used Semi-Active Control (SAC) devices. These dampers use a fluid containing magnetic particles that change their viscosity when subjected to a magnetic field. The viscosity can be controlled in real-time by varying the current applied to the electromagnet within the damper. Control algorithms are responsible for adjusting the amount of this current at each timestep.

Reinforcement learning (RL) is a subset of machine learning that teaches agents how to solve tasks by trial and error. RL has been successfully used to find optimal cooling strategies in datacenters, guiding self-driving cars and controlling vehicle suspension systems. Despite this success, research on the application of RL to SAC algorithm development has been surprisingly limited. In this work, we utilize an actor-critic, deep RL algorithm named TD3.

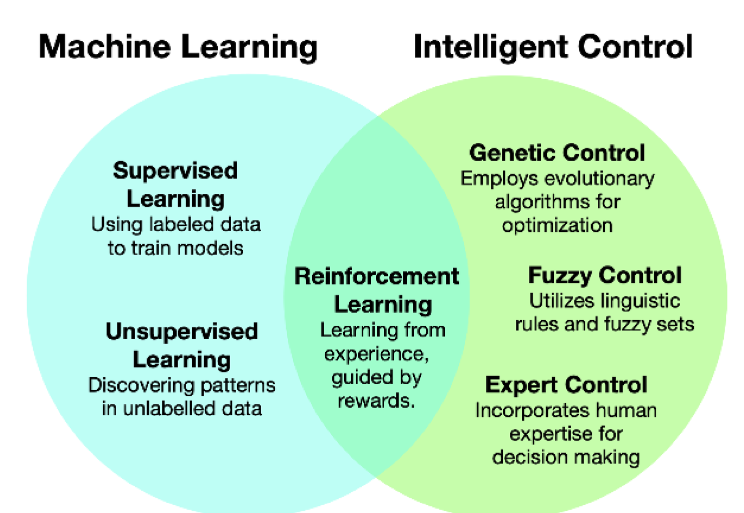

Figure (1): Reinforcement Learning, relation with ML and IC

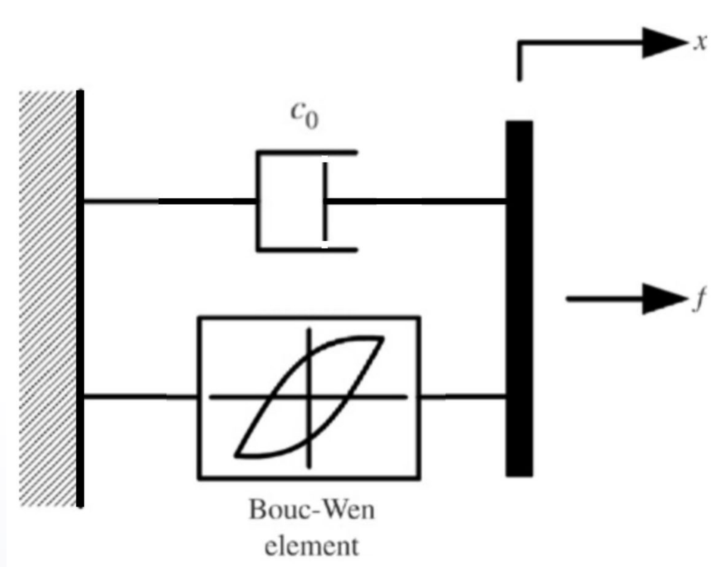

Figure (2): MR damper, mechanical model

Case Study Building

The case study structure is a 9-story steel-frame building with a single level basement, located in Los Angeles (LA), and designed using the post-Northridge standard connections in conformance with the provisions of FEMA 267 Venture (1995). As seen in Fig. 1a the frame structure includes 5 bays of equal spans in both NS and EW directions.

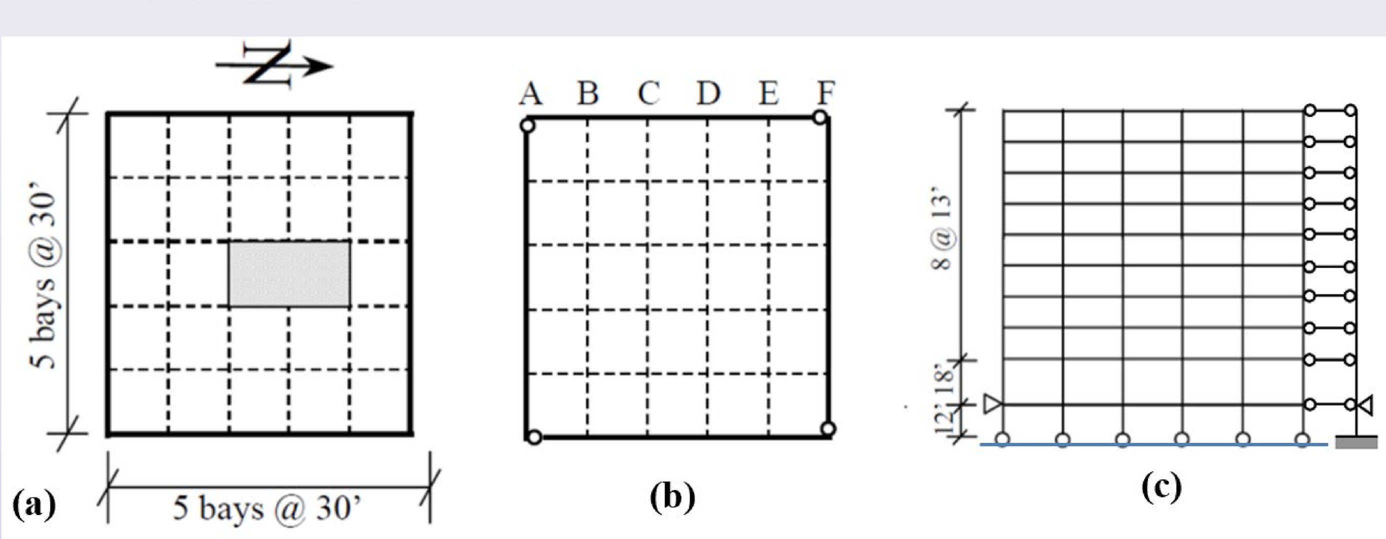

Figure (3): Layout of model building; a) plan view and dimensions, b) beam-column connections in plan, and c) elevation view of a perimeter frame

Conclusions

The results of this study suggest that the TD3 algorithm is effective for semi-active control of structures.

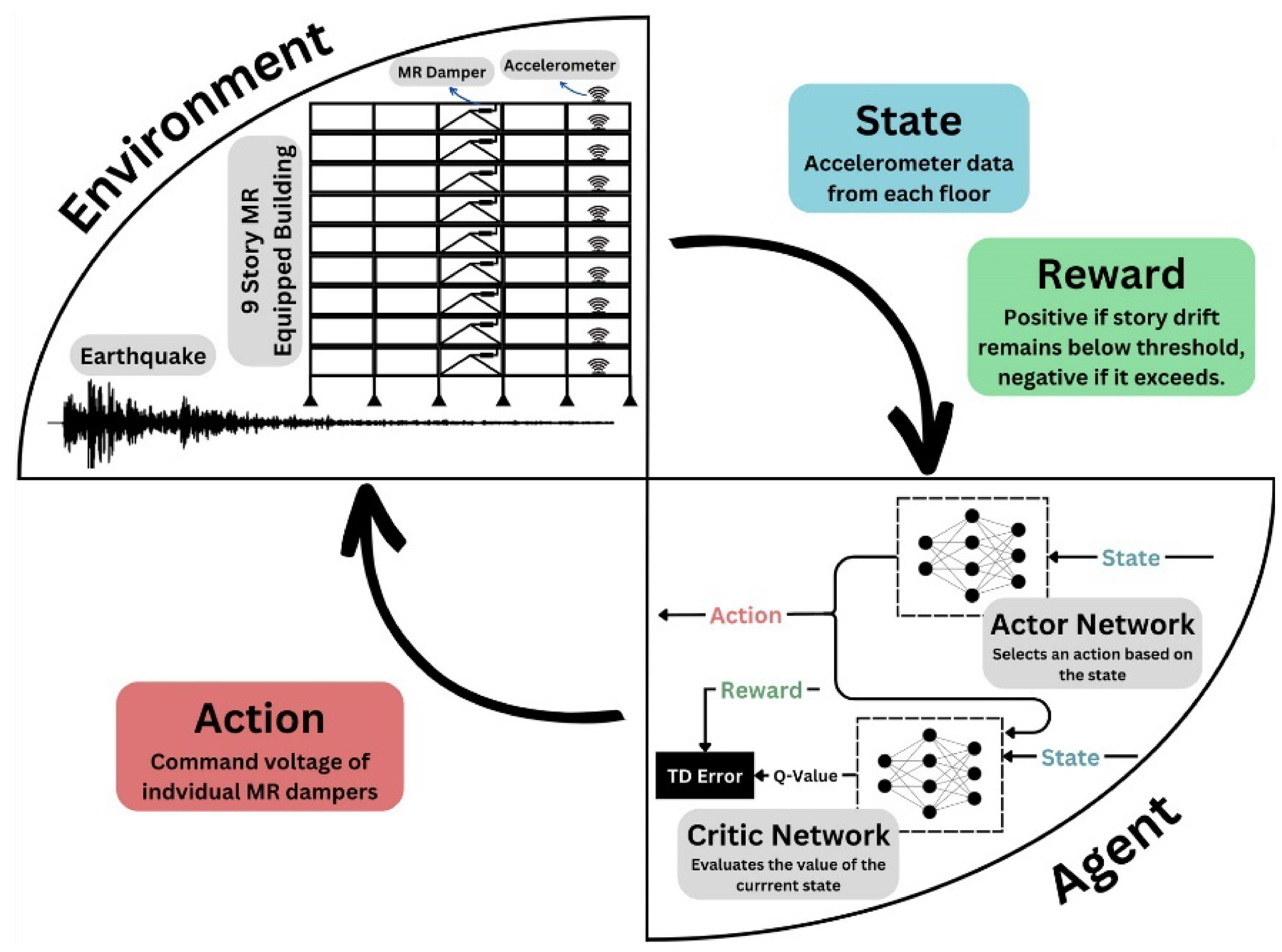

Figure (4): Applying an actor-critic RL model for SAC of a 9 story building equipped with MR dampers

Proposed Method

The RL environment comprises a 9-story building equipped with 9 MR-dampers and subjected to an earthquake. At each discrete time step (0.001 seconds), the current ground acceleration is applied to the building, leading to a transition to a new state. This state is measured via the 10 accelerometers located at each floor. This data is fed into the RL neural network which in turn outputs an action in the form of a 9-element vector representing the command voltage magnitude to be applied to MR damper. The agent then receives a reward based on its selected action, i.e. how well the story drifts have been minimized. After repeating this process for 20 episodes (a total of 400,000 time steps). The RL model had learned optimal actions depending on each state.

Results

The RL method was tested by evaluating its performance under two recorded earthquakes (i.e., LA01 and LA02). The performance of the method was also compared with the passive damper (i.e., no MR action), and skyhook based control systems. Figs. 4a and 4b show the time history of roof drift ratio in buildings of different control strategies under two tested earthquakes. The boundaries of the threshold drift ratio (0.75%) are also shown in Figs. 4a and 4b with the horizontal dashed lines in red. The drift ratios below and above the threshold limit of 0.75% are designated with green and red zones, respectively. As it can be seen, the performance of the TD3 control method in response mitigation of the structure is superior. Table 4 includes the peak interstory drift and the relative time duration over which the magnitude of the drift ratio exceeded the permissible limit of 0.75% at representative Stories 1 (above the basement), 5, and 9.

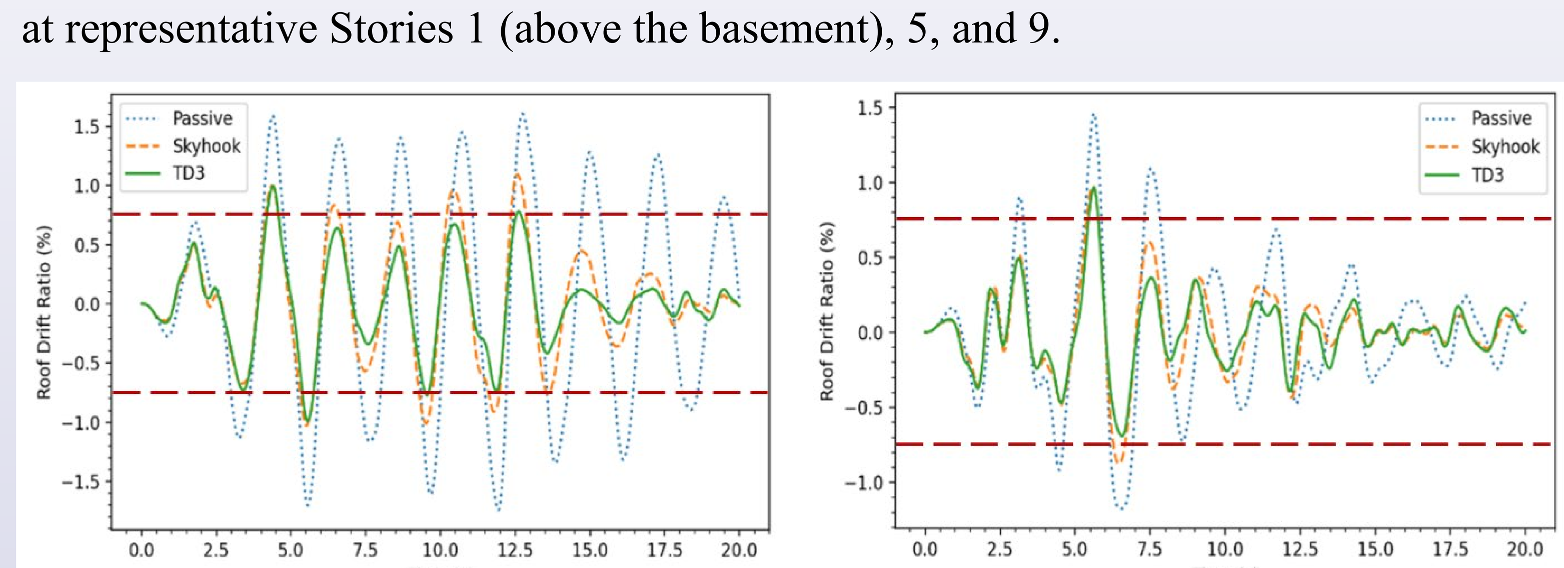

Figure (5): Comparison of different control methods in response mitigation of structure; (a) LA01 Earthquake, (b) LA02 Earthquake

Table (1): Response control of various algorithms under LA02 Earthquake

Story	Peak interstory drift (mm)			Relative time duration of vibrations within the red zone (%)		
	Passive	Skyhook	TD3	Passive	Skyhook	TD3
1	109	71	59	8.9	3.1	2.5
5	60	44	43	8.2	2.0	1.8
9	53	41	27	5.8	0.7	0.0