Deep Reinforcement Learning Control of an Oscillating Hydrofoil to Maximize Power Extraction

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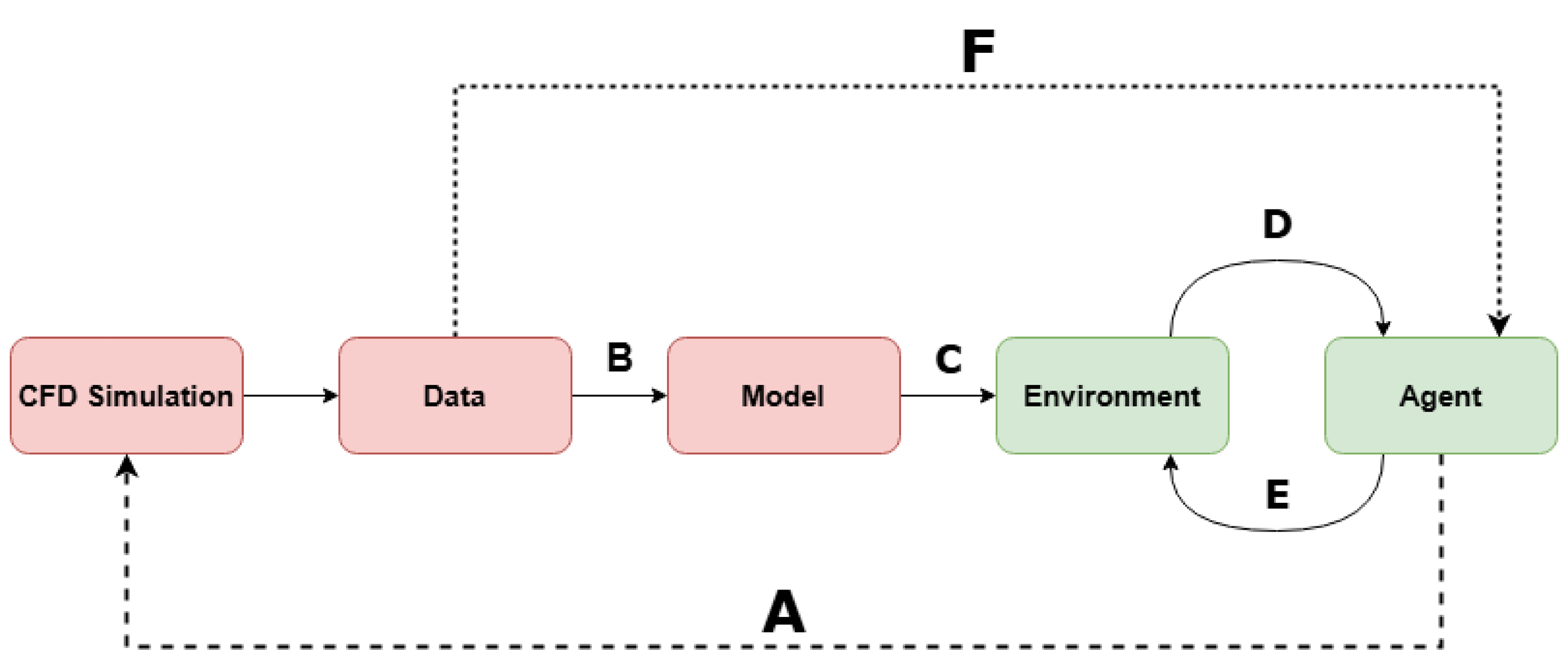
Introduction

Deep reinforcement learning has become a promising new approach in place of traditional control for achieving high performance of engineering systems.

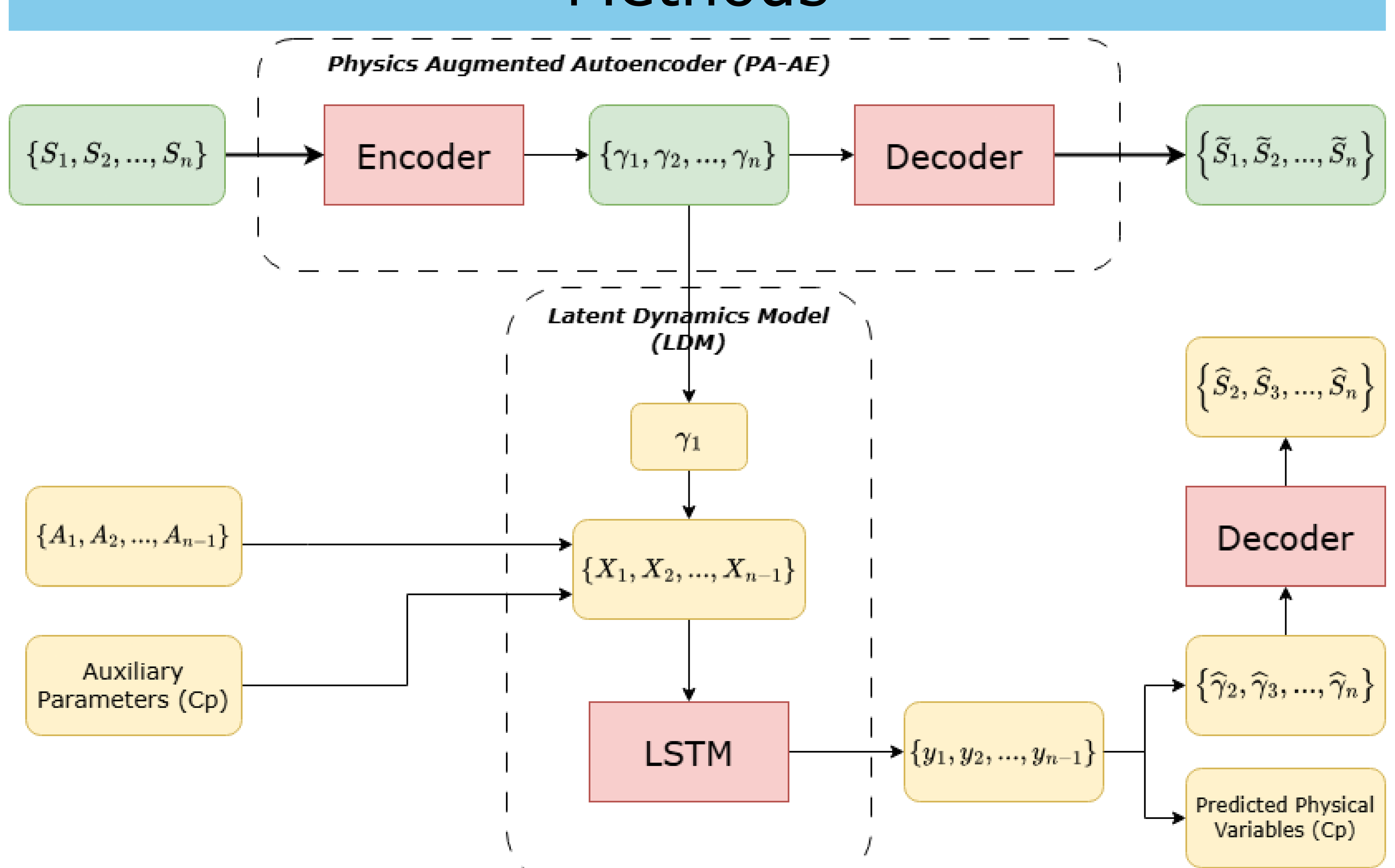
- Fluid mechanics systems are nonlinear and high-dimensional
- Deep RL provides opportunity to simplify process of creating optimal control methods
- High dimensionality challenges training process, requires large number of costly interactions with full environment
- We demonstrate potential benefits of deep RL to train active control to extract maximum power from an oscillating hydrofoil
- Training relies on a low-dimensional model of the environment, which greatly improves time of training compared with model-free RL approaches
- In this poster, we present the results of the trained autoencoder



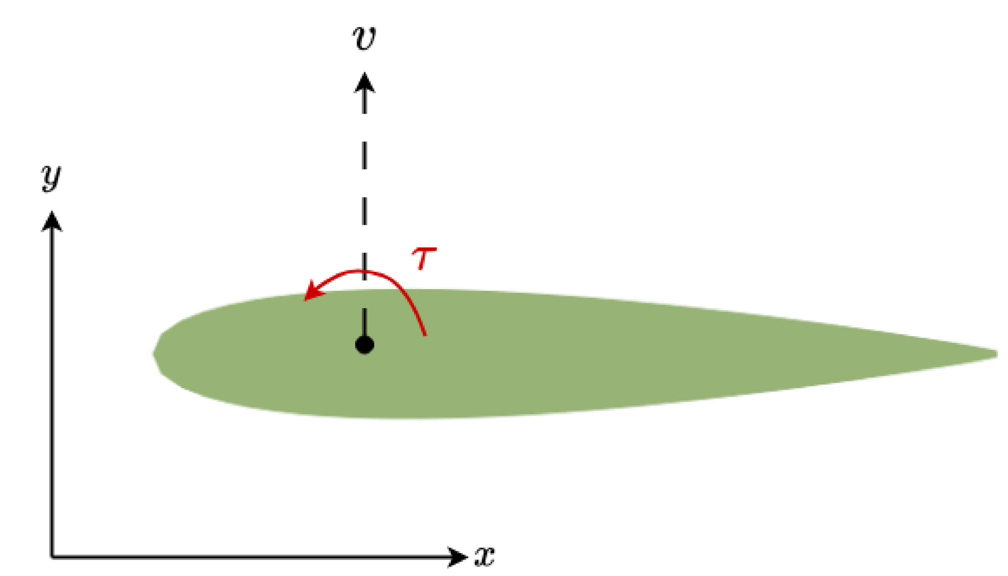
Reinforcement Learning Structure

Comparison between the implemented MBRL structure and typical model-free RL structure. MBRL structure is shown as solid lines, typical model-free structure shown as dashed lines

Methods

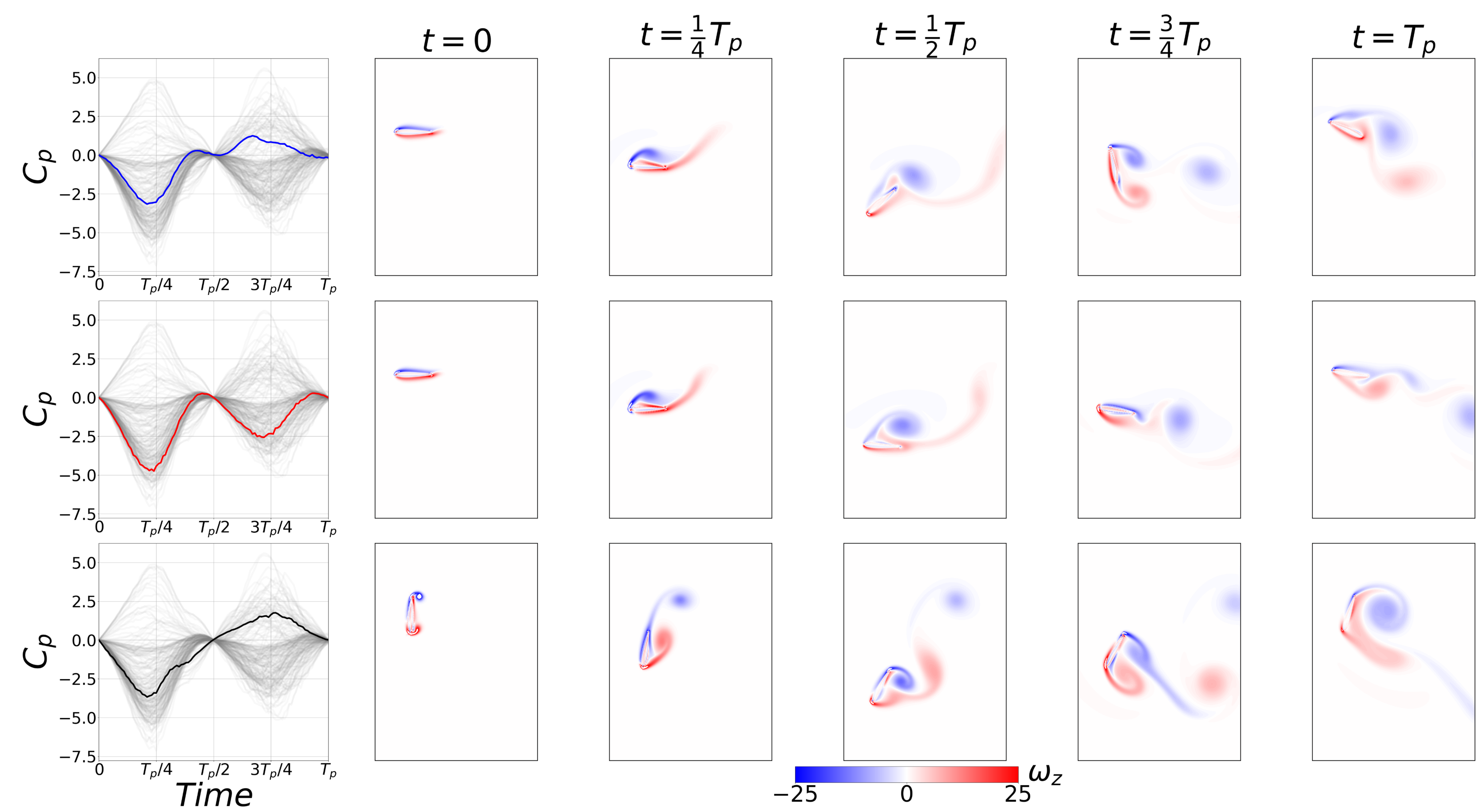


Results



CFD Model of Hydrofoil

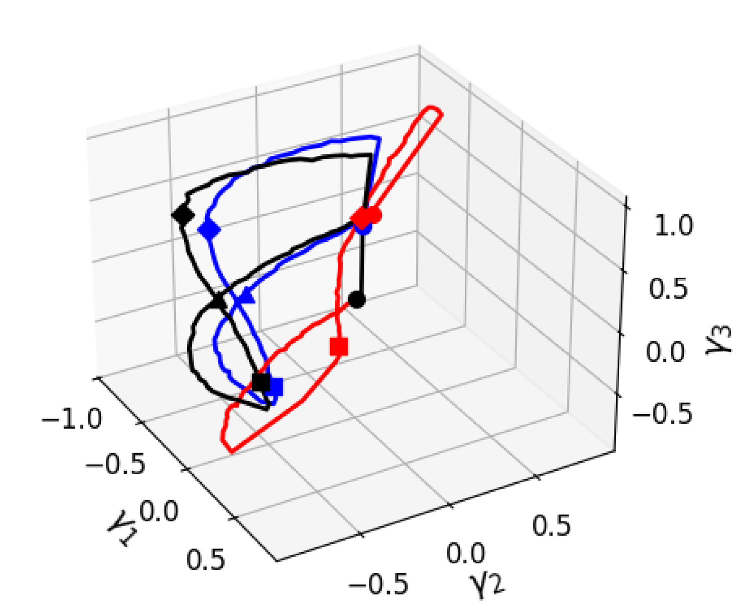
- Fixed sinusoidal heaving motion at preset frequency and amplitude
- Random starting angle, random torque applied for pitching
- Data collected on vorticity field, pitching angular acceleration and power coefficient (Cp)



CFD Simulation Results

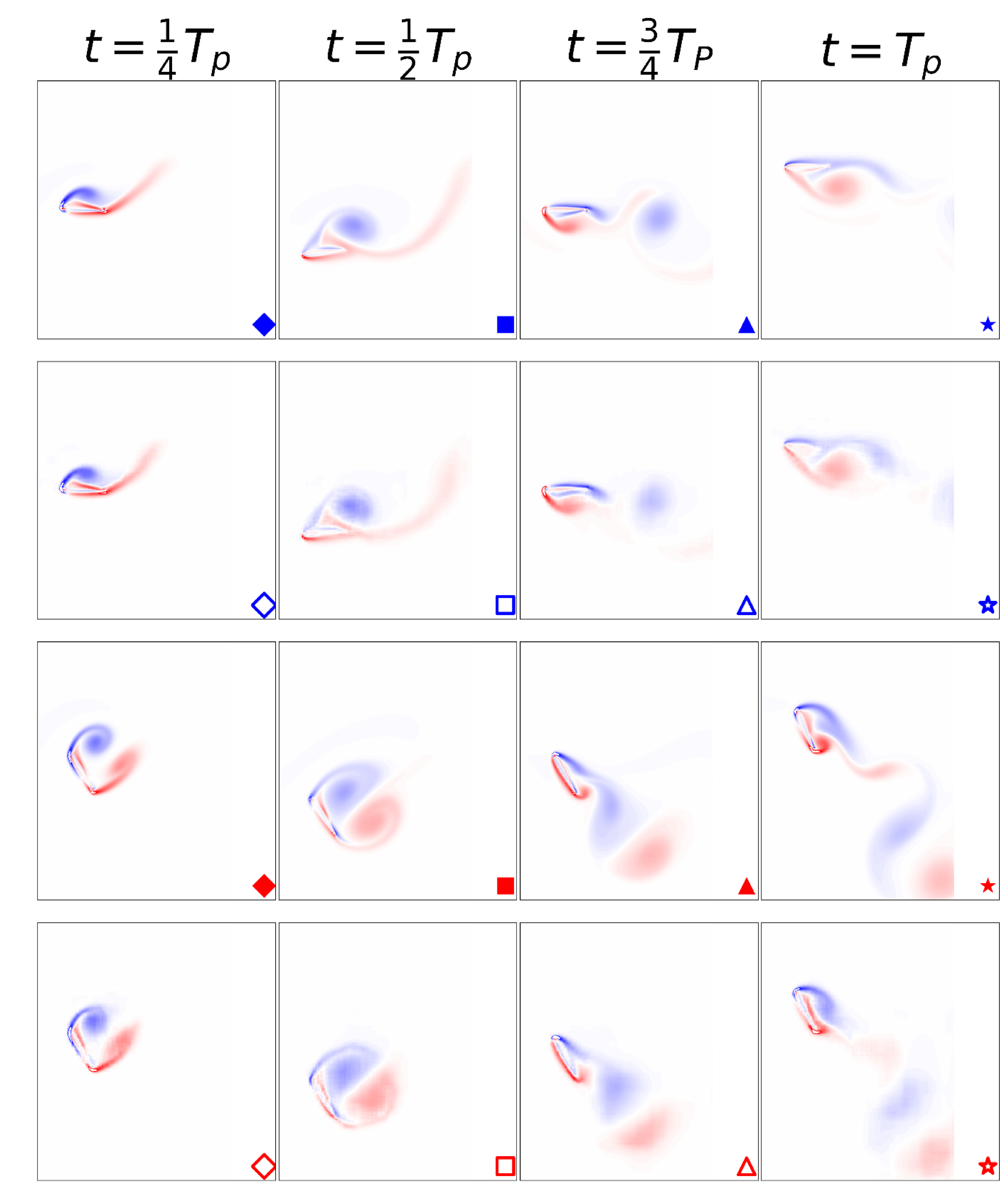
Conclusions & Next Steps

- Demonstrated ability of AE to compress vorticity field into latent space and accurately reconstruct vorticity and power
- Analyze various training data control methods to obtain richer data set for training
- Train LSTM to predict latent dynamics based on control actions
- Train reinforcement learning policy to learn optimal methods for control
- Add disturbances and unsteady flow to CFD model and investigate RL model robustness



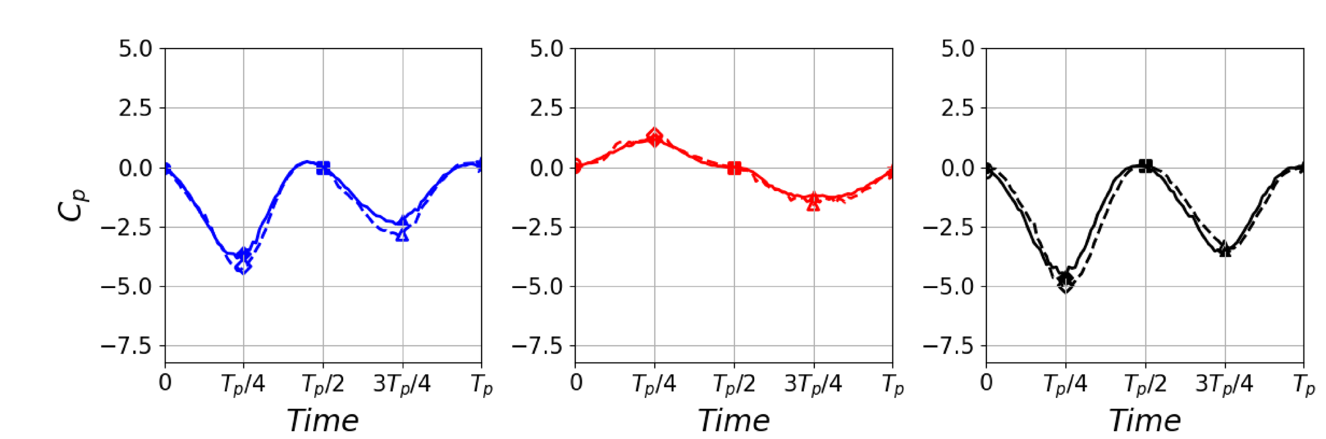
Latent Space Trajectories

Analysis



Autoencoder Vorticity Reconstruction

Solid shapes represent the true vorticity while hollow shapes show the autoencoder reconstruction, with two test cases shown



Autoencoder Power Reconstruction

Acknowledgements & References

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Zhecheng Liu, Diederik Beckers, Jeff D. Eldredge. "Model-Based Reinforcement Learning for Control of Strongly-Disturbed Unsteady Aerodynamic Flows." (2024).