A Neural Differentiable Framework for Efficient Simulation and Rapid Optimization of Energy Harvesters

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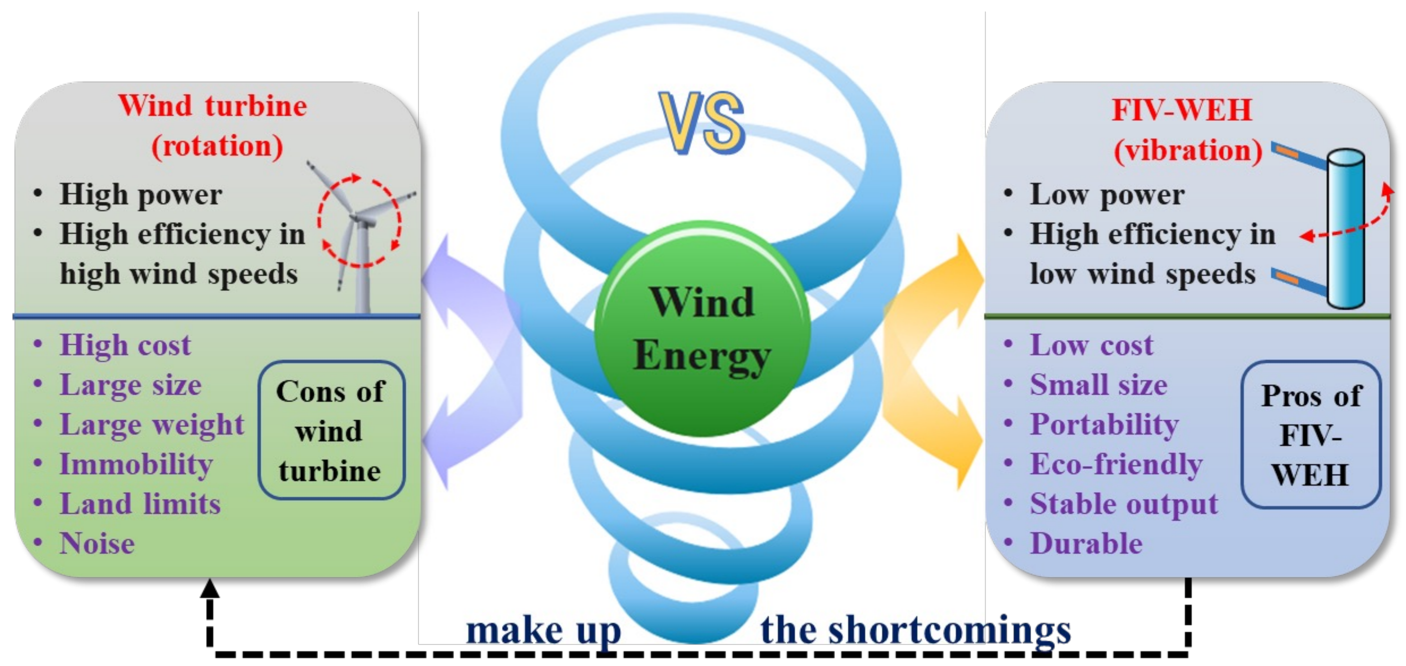
※Motivation

In response to the rapid growth of energy consumption, renewable energy harvesters have emerged as a powerful technique for providing sustainable energy and achieving carbon neutrality, including turbines, hydrofoils, flapping foils, flow-induced vibrations (FIV) energy harvesters, etc.

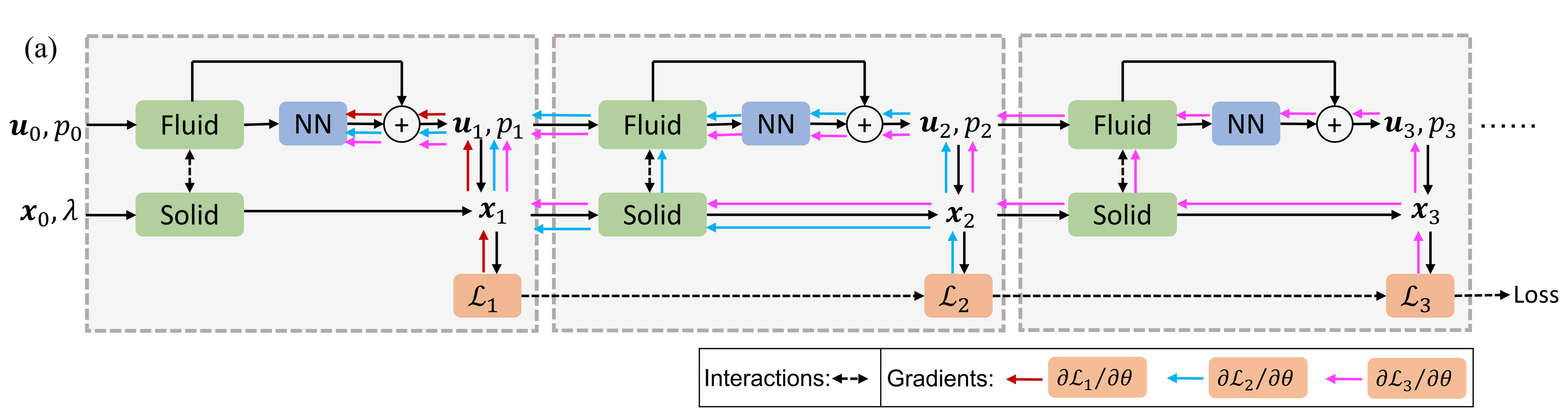
- The harvesters requires effective simulation at design and fast optimization in operation. However, classical computational fluid dynamics (CFD)-based solvers are too expensive.
- The ever-increasing data availability and rapid developments in deep learning (DL) have opened new avenues to tackle these challenges.
- A fully **differentiable programming** framework for simulating harvesters based on JAX is established. Different DL models can be integrated and optimized within the neural solver in an end-to-end manner.
- The FIV energy harvester is simulated by this framework to demonstrate the merit and potential.

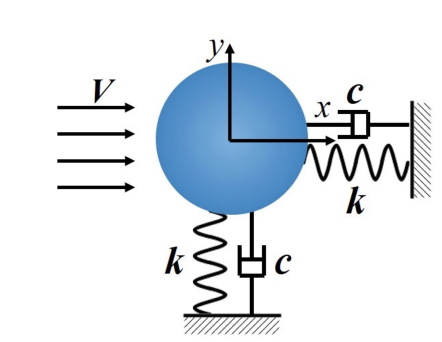


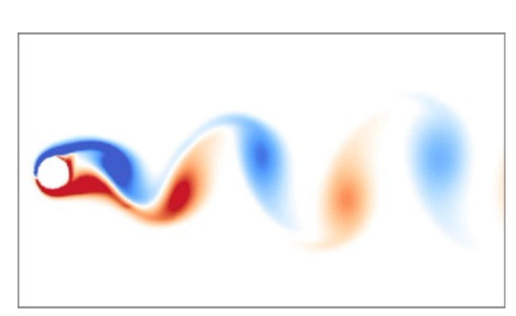
※Method

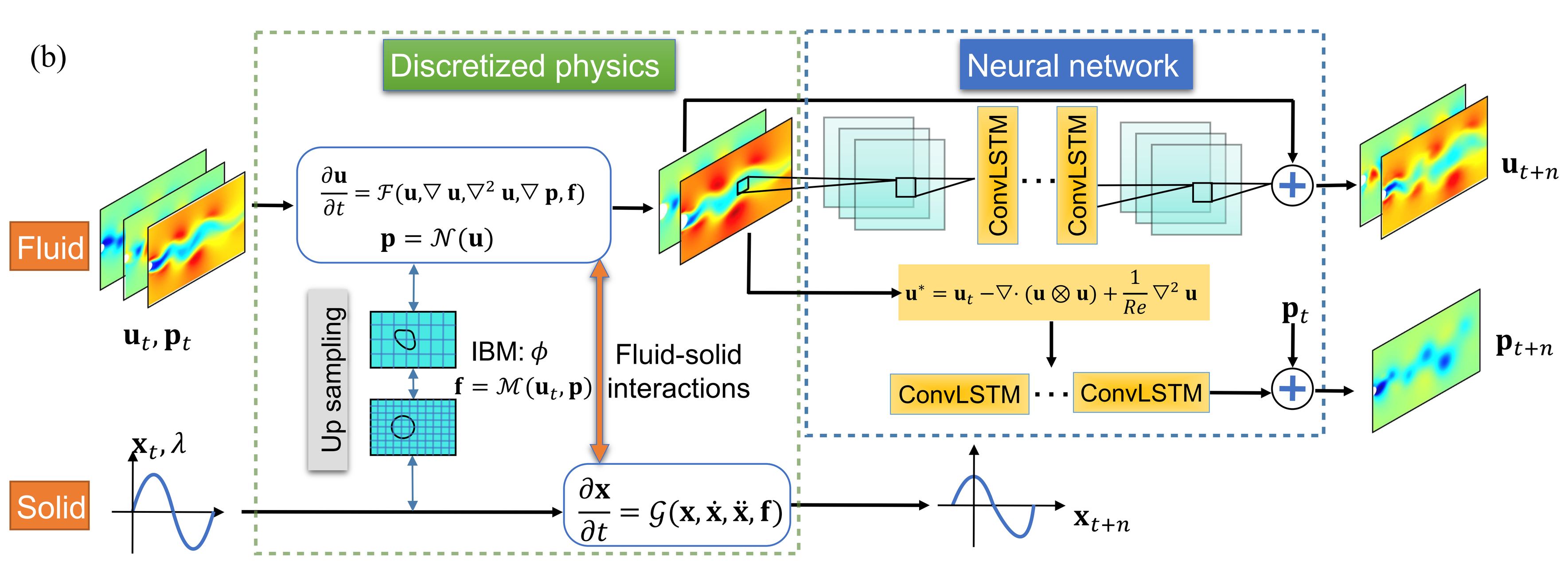
FSI problems are governed by series of coupled partial differential equations (PDEs), which are temporal-spatial nonlinearity.

$$\frac{\partial \mathbf{u}}{\partial t} = -\nabla\cdot(\mathbf{u}\otimes\mathbf{u}) + \frac{1}{Re}\nabla^2 \mathrm{u} - \frac{1}{\rho}\nabla p + \mathbf{f} \quad \& \quad \nabla\cdot\mathbf{u}{=}0 \quad \& \quad \mathbf{M}\frac{\partial^2 \mathbf{x}}{\partial t^2} + \mathbf{C}\frac{\partial \mathbf{x}}{\partial t} + \mathbf{Kx} = \mathbf{f}$$







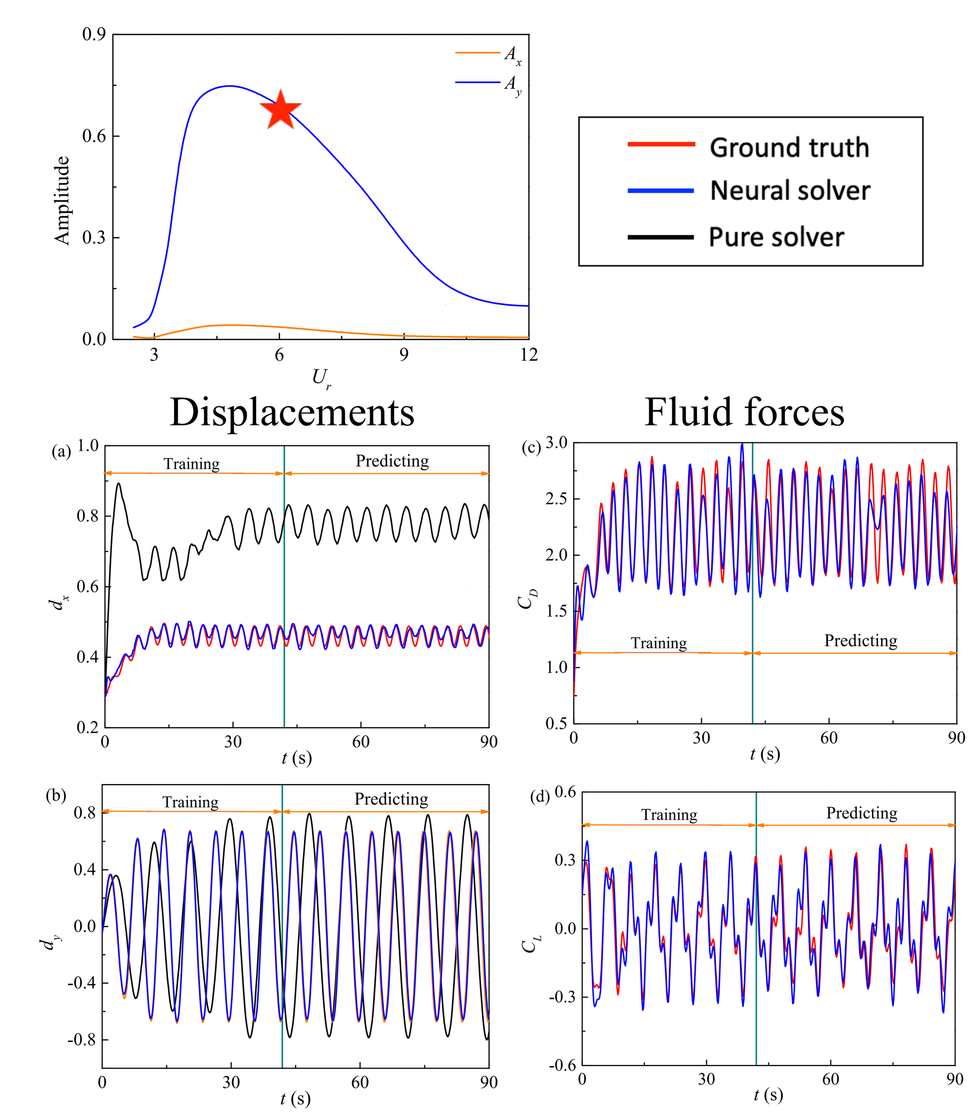


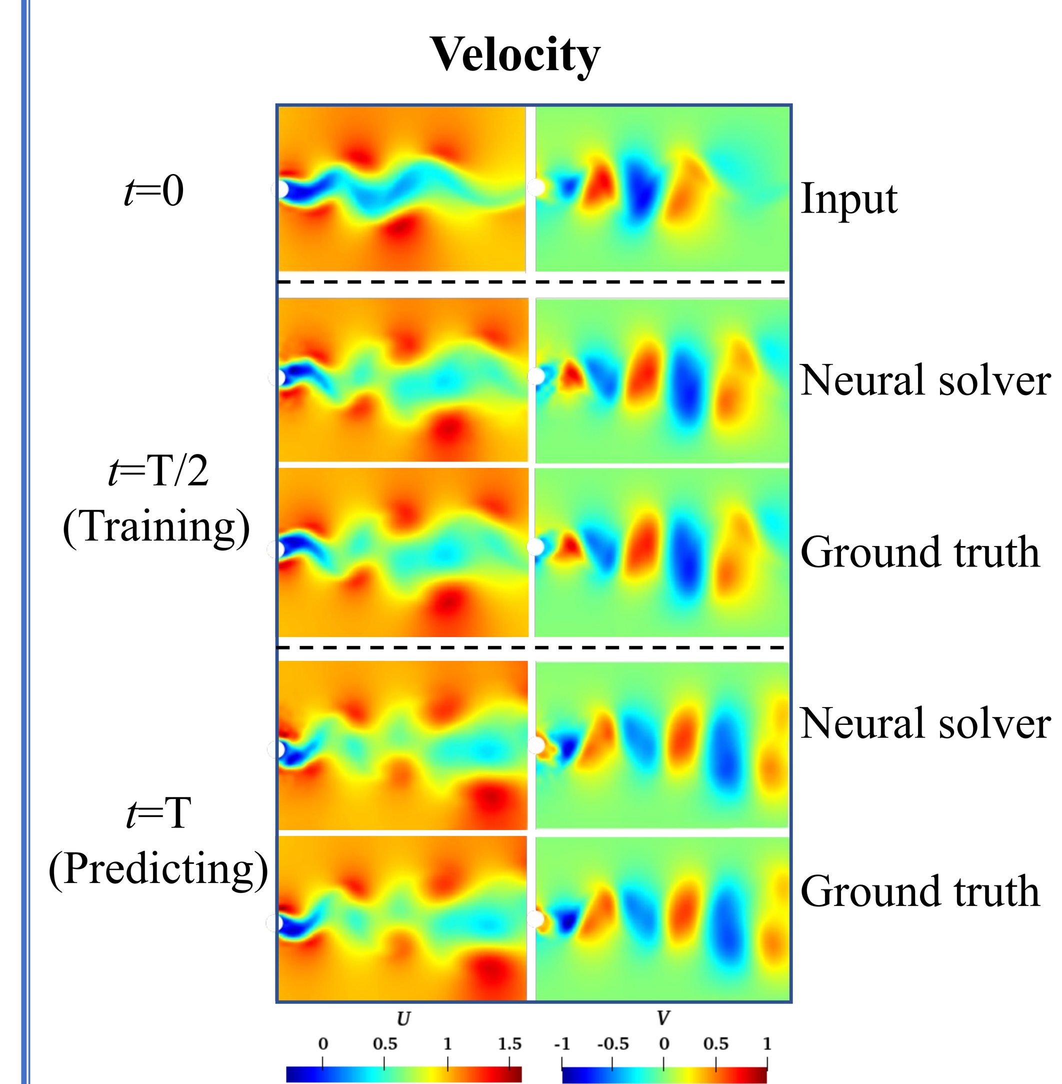
(a) Overview of the neural solver architecture, where ‘Fluid’ and ‘solid’ denote the physical governing PDEs, ‘NN’ represents neural network; (b) The detailed components in one-step neural FSI solver.

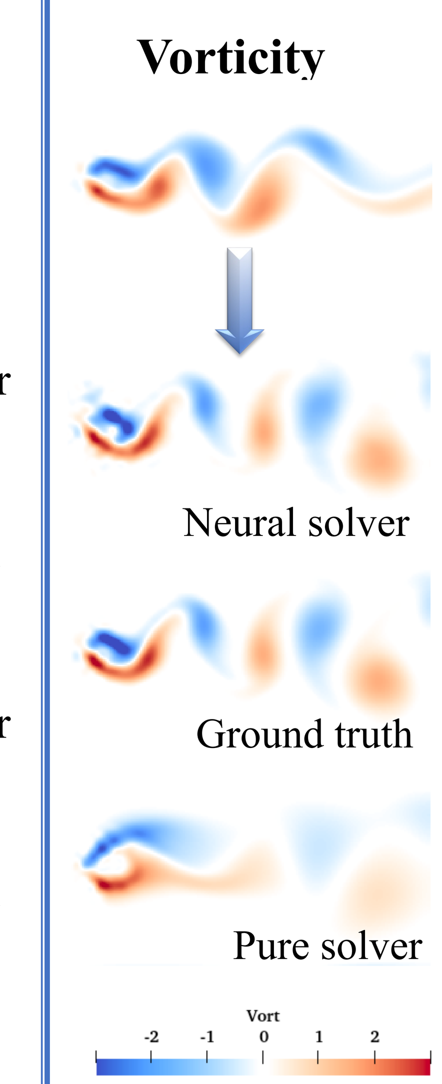
Automatic differentiation (AD); Just-in-time (jit) Compilation

※Results

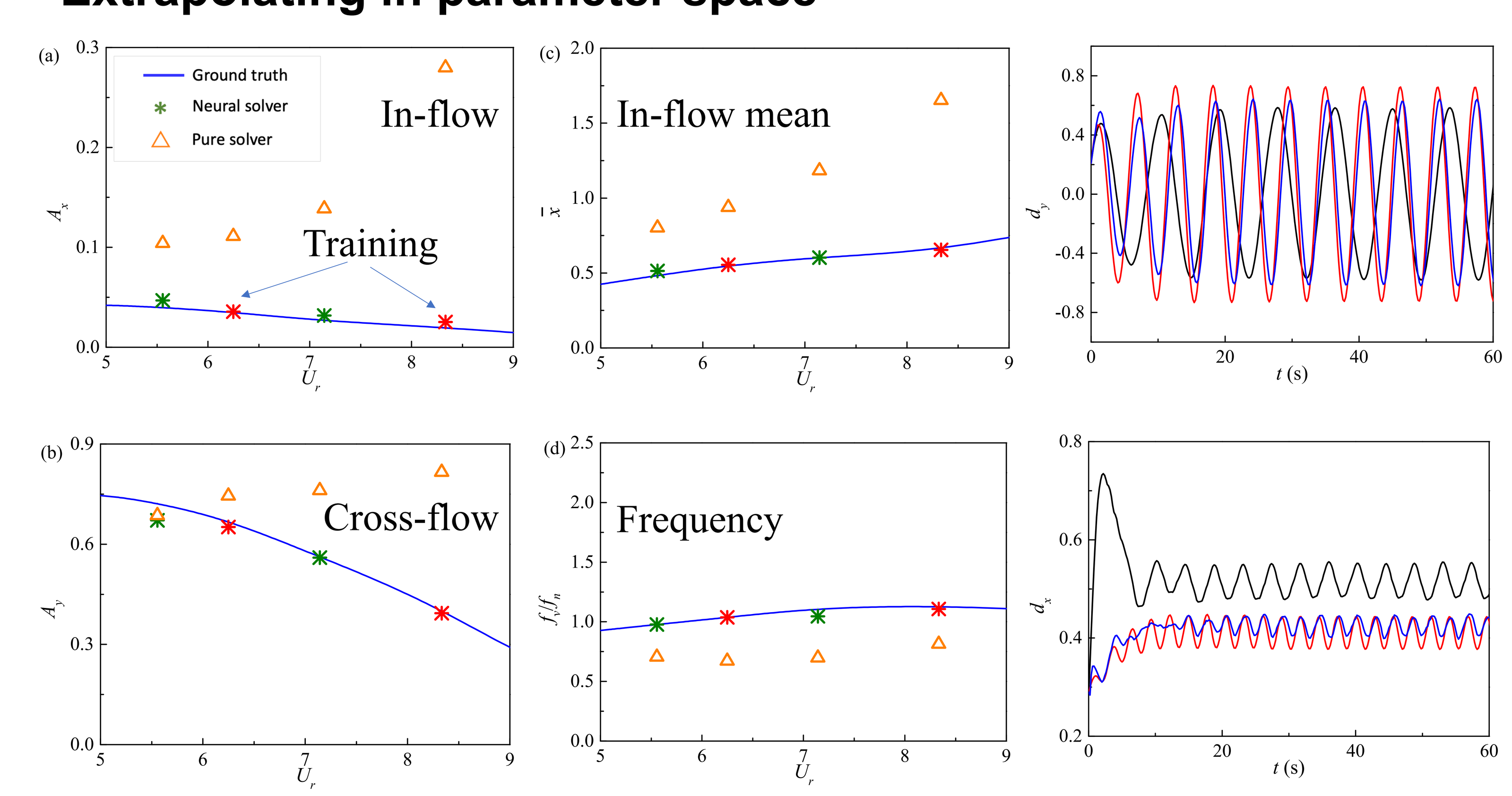
☞ Forecasting in time sequence



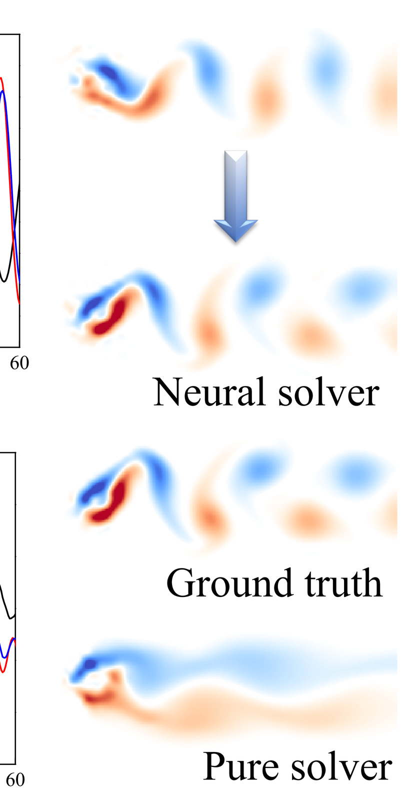


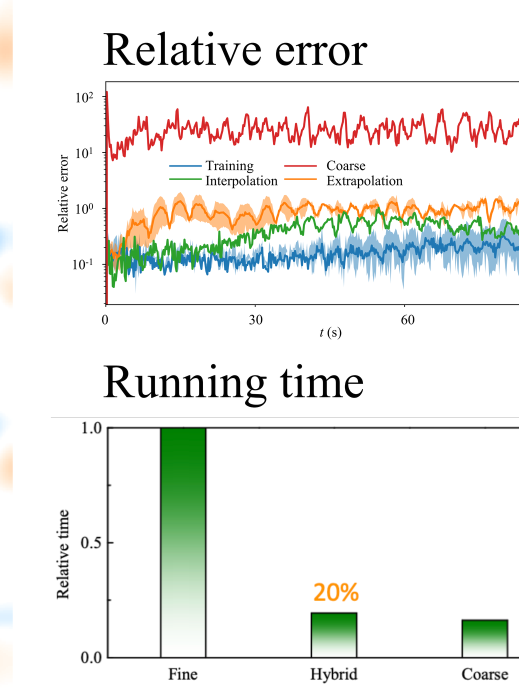


☞ Extrapolating in parameter space



☞ Model evaluation





※Conclusion

- Integrating traditional numerical solvers into deep neural networks (DNN) to enable effective data-driven modeling.
- Hybrid framework can accurately predict the structural responses and flow patterns (including parameters space).
- Solving the complex and expensive FSI problems is much faster (20% for 8× coarse).
- The error accumulation can be partially eliminated.
- Get rid of the dependency on grid size and quality.
- It can be used to design and optimize the energy harvester in a very fast way.

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