Modeling vortex-induced vibrations displacement with phenomena-informed neural network

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Abstract. Vortex-Induced Vibrations (VIV), as a phenomenon, can be modeled by a dynamical system (single equation) that includes a term that is negatively proportional to the velocity to account for the energy transfer from the flow to the structure, and another term that is proportional to an odd power of the velocity to yield limit cycle oscillations. We implement a data-driven system discovery, referred to as Phenomena-Informed Neural Network, to identify the coefficients in the representative equation of these phenomena. The training data is obtained from direct numerical simulations of the Navier-Stokes equations. The representative equation can be effectively used to assess VIV control strategies.

Introduction

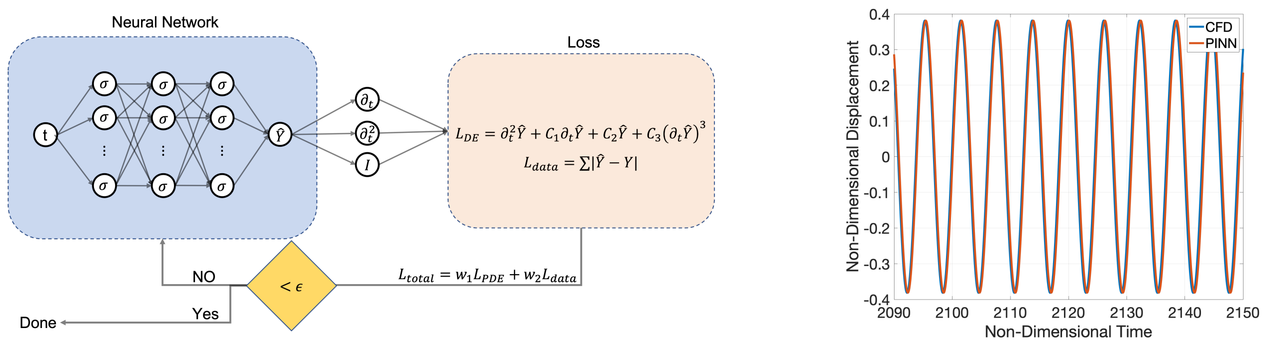
In the context of vortex-Induced Vibrations (VIV), energy transfer from the flow to the moving structure requires positive excitation represented by a negative damping term. Furthermore, limiting the amplitude of these vibrations requires a damping term proportional to a higher power of the velocity, e.g. cubic damping term [1]. As such, VIV oscillation amplitudes, Y, can be modeled or predicted by a phenomenological model such as the Rayleigh oscillator:

$$\ddot{Y} + C_1\dot{Y} + C_2 Y + C_3\dot{Y}^3 = 0 \qquad (1)$$

Hajj et al. [1] combined spectral analysis of data from direct numerical simulations of the Navier-Stokes equations with an approximate solution of equation (1) to identify C_1, C_2, and C_3. Here, we implement a data-driven system identification (discovery) of equation (1), to be referred to as Phenomena-informed Neural Networks (PINN). The concept is to combine the phenomena-representing equation (1) with available data to train a Neural Network and identify C_1, C_2, and C_3.

Results and Discussion

As schematically presented in figure 1a, the implemented Neural Network consists of four hidden layers with 30 nodes per layer. A total loss function, L_{total}, is used to update all the trainable parameters, i.e., weights, biases, and C_1, C_2, and C_3. This loss function is the weighted sum of L_{data}, defined as the error between the predicted and simulated displacement values represented respectively by $\hat{Y}$ and Y, and L_{DE}, defined as the error resulting from using $\hat{Y}$ in equation (1). Based on an error threshold criterion, it took $264,000$ iterations to identify the trainable parameters. Figure 1b compares time series of numerically simulated and PINN-predicted oscillation amplitudes. The plot shows excellent agreement in the frequency and amplitude ($< 0.1\%$) of the two time series.



(a) (b)

Figure 1: (a) PINN implementation, and (b) comparison of CFD- and PINN-generated time series of the VIV response. Re=110. Details of numerical simulations and conditions are provided in Hajj et al. [1].

References

[1] Hajj M.R., Mehmood A., Akhtar I. (2021) Single-degree-of-freedom model of displacement in vortex-induced vibrations. *Nonlinear Dynamics* **103.2**:1305-1320.