MORTech 2025
7th International Workshop on Model Order Reduction Techniques
Cueto, Chinesta, Néron, Ladevèze, Eds.
26-28 November 2025 | Zaragoza, Spain

Latent-Lagrangian Neural Networks for Model-Order Reduction of Nonlinear Dynamical Systems

Anand Kumar Agrawal[1], Louen Pottier[1], Anders Thorin[1]

[1]Université Paris-Saclay, CEA, List, F-91120, Palaiseau, France
e-mail: anand-kumar.agrawal@cea.fr

ABSTRACT

Developing accurate physics-based models and their numerical simulation for high-dimensional nonlinear dynamical systems remains complex and computationally demanding. Addressing this difficulty using purely data-driven approaches often leads to data inefficiency, fails to respect the underlying physics, and produces models that fail to generalize well. This work proposes a Latent-Lagrangian Neural Network (L-LNN), which can be seen as a variant of a Lagrangian NN [1] modified so that the Lagrangian is a learned NN in a low-dimensional latent space. It can also be seen as an extension of Latent-Energy Based NN (LEBNN) [2] to dynamics. Therefore, this approach enforces the governing mathematical model while being cost effective.

Specifically, the neural networks are designed to satisfy the structure of the physics-based model through position-dependent mass and stiffness matrices which are written as Hessian of parameterized neural networks representing latent kinetic and potential energies, respectively. The damping matrix is modelled via a position-dependent linear combination of the mass and stiffness matrices (position-dependent Rayleigh damping). The above-mentioned approach ensures good predictive capability as well as computational and data efficiency. The training is performed by embedding energy and dissipation-aware terms into the loss function of the neural networks through mean squared error in the true and predicted force. The kinetic energy is an NN whose architecture is forced to be a quadratic form of the generalized velocities.

The results are illustrated on two nonlinear dynamical systems: a two-degree-of-freedom (2-dof) system with non-convex potential energy, and a 20-dof beam undergoing very large deflections. The trainings are performed on datasets containing several time series of generalized coordinates that are generated by randomly varying the external force and the initial conditions.

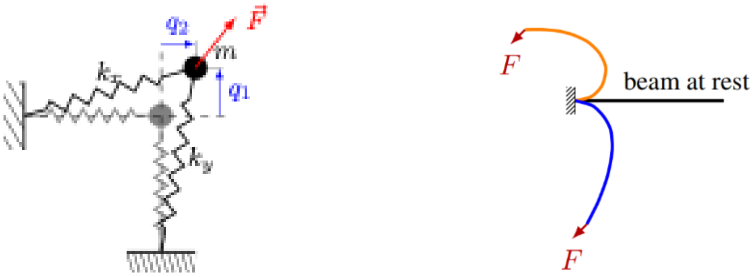

Figure 1. Two nonlinear dynamical systems used to demonstrate the relevance of L-LNN

The numerical simulation of the reduced-order model obtained from the learned latent energies for the 2-dof system was able to successfully predict the dynamic response of the system with good accuracy: for instance, a relative error of 0.7% for a 10-second time series, see Fig. 2. Additionally, the topology of the kinetic and potential energies, learned simultaneously, is sound (see Fig. 3).

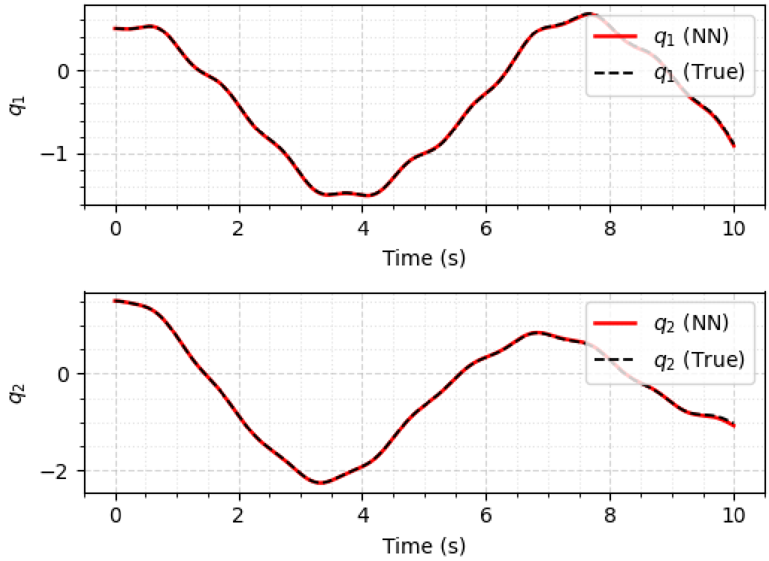

Figure 2. System response comparison between the true and learned latent models for arbitrary input and initial states for the 2-dof system.

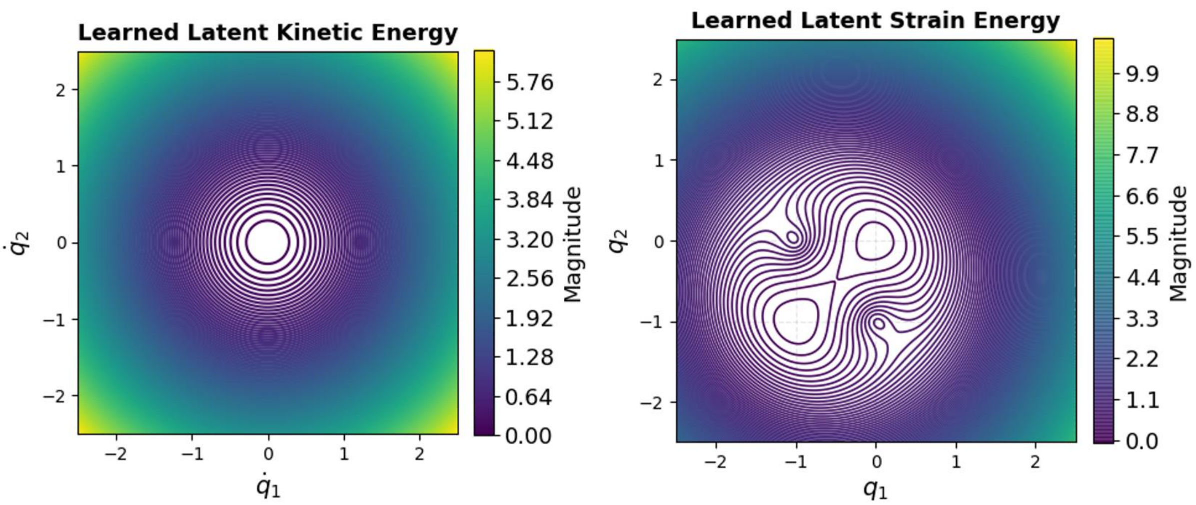

Figure 3. Contours of the learned kinetic and potential energies in the latent space for the 2-dof system

These encouraging results motivate its application to model order reduction of more complex nonlinear dynamical systems and their coupling to traditional numerical solvers.

REFERENCES

[1] Cranmer M, Greydanus S, Hoyer S, Battaglia P, Spergel D, Ho S. Lagrangian neural networks. arXiv preprint arXiv:2003.04630. 2020 Mar 10.

[2] Pottier, Louen, Anders Thorin, and Francisco Chinesta. "Latent-Energy-Based NNs: An interpretable Neural Network architecture for model-order reduction of nonlinear statics in solid mechanics." *Journal of the Mechanics and Physics of Solids* 194 (2025): 105953.