# Model-based emulators and machine learning (ML) methods in nuclear physics

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# Emulators as part of computational research in nuclear physics

- Recent years have witnessed success in emulating nuclear bound and continuum states calculations.
- Many other nuclear physics topics (important for FRIB, Jlab, EIC, and astrophysics) are waiting to be explored: nuclear resonances, responses, and reactions, (time-dependent) density functional theory, bridging theory and experiment, and more.
- Synergy between ML and model-driven emulators expands their capability (or one way to achieve physics informed ML).

  "Deep learning-based reduced order models (DL-ROMs) have been recently proposed to overcome common limitations shared by conventional reduced order models (ROMs) – built, e.g., through proper orthogonal decomposition (POD) – when applied to **nonlinear time-dependent** parametrized partial differential equations (PDEs)." from Stefania Fresca, Andrea Manzoni (2022) [2101.11845]
- In nuclear physics, our recent work combines Gaussian process and model-driven emulators for quantum three-body scattering.

  Xilin Zhang, R. Furnstahl (2022) [2110.04269 ]
- The synergy is a new research direction in the field of model order reduction and has great potential in nuclear physics as well.

  Jan S. Hesthaven, Cecilia Pagliantini and Gianluigi Rozza (2022)[https://doi.org/10.1017/S0962492922000058]

# An (incomplete) list of works

- Discrete spectrum:
  - Dillon Frame et. al., Phys.Rev.Lett. 121 (2018) 3, 032501 [1711.07090]
  - S. König et. al. , Phys.Lett.B 810 (2020) 135814 [1909.08446]
  - Andreas Ekström and Gaute Hagen, Phys.Rev.Lett. 123 (2019) 25, 252501 [1910.02922]
  - P. Demol et.al., Phys.Rev.C 101 (2020) 4, 041302 [ 1911.12578 ]
  - Avik Sarkar and Dean Lee, Phys.Rev.Lett. 126 (2021) 3, 032501 [ 2004.07651 ]
  - Sota Yoshida and Noritaka Shimizu, PTEP 2022 (2022) 5, 053D02 [ 2105.08256]
  - Margarida Companys Franzke et. al., Phys.Lett.B 830 (2022) 137101 [2108.02824 ]
  - T. Djärv et.al., Phys.Rev.C 105 (2022) 1, 014005 [ 2108.13313]
  - Pablo Giuliani et. al., [ 2209.13039 ]
  - Nuwan Yapa and S. König, Phys.Rev.C 106 (2022) 1, 014309 [ 2201.08313 ]
  - Amy L. Anderson et. al., Phys.Rev.C 106 (2022) 3, L031302 [ 2206.14889]

- Introduction of model order reduction methods (many good references there):
  - J.A. Melendez et. al., J.Phys.G 49 (2022) 10, 102001 [ 2203.05528 ]
  - Edgard Bonilla et. al., [ 2203.05284]

- Continuum states:
  - R.J. Furnstahl et. al., Phys.Lett.B 809 (2020) 135719 [ 2007.03635 ]
  - Dong Bai and Zhongzhou Ren, Phys.Rev.C 103 (2021) 1, 014612 [2101.06336]
  - J.A. Melendez et.al., Phys.Lett.B 821 (2021) 136608 [ 2106.15608]
  - C. Drischler et.al., Phys.Lett.B 823 (2021) 136777 [ 2108.08269]
  - Xilin Zhang and R.J. Furnstahl, Phys.Rev.C 105 (2022) 6, 064004 [ 2110.04269]
  - Dong Bai, Phys.Rev.C 106 (2022) 2, 024611

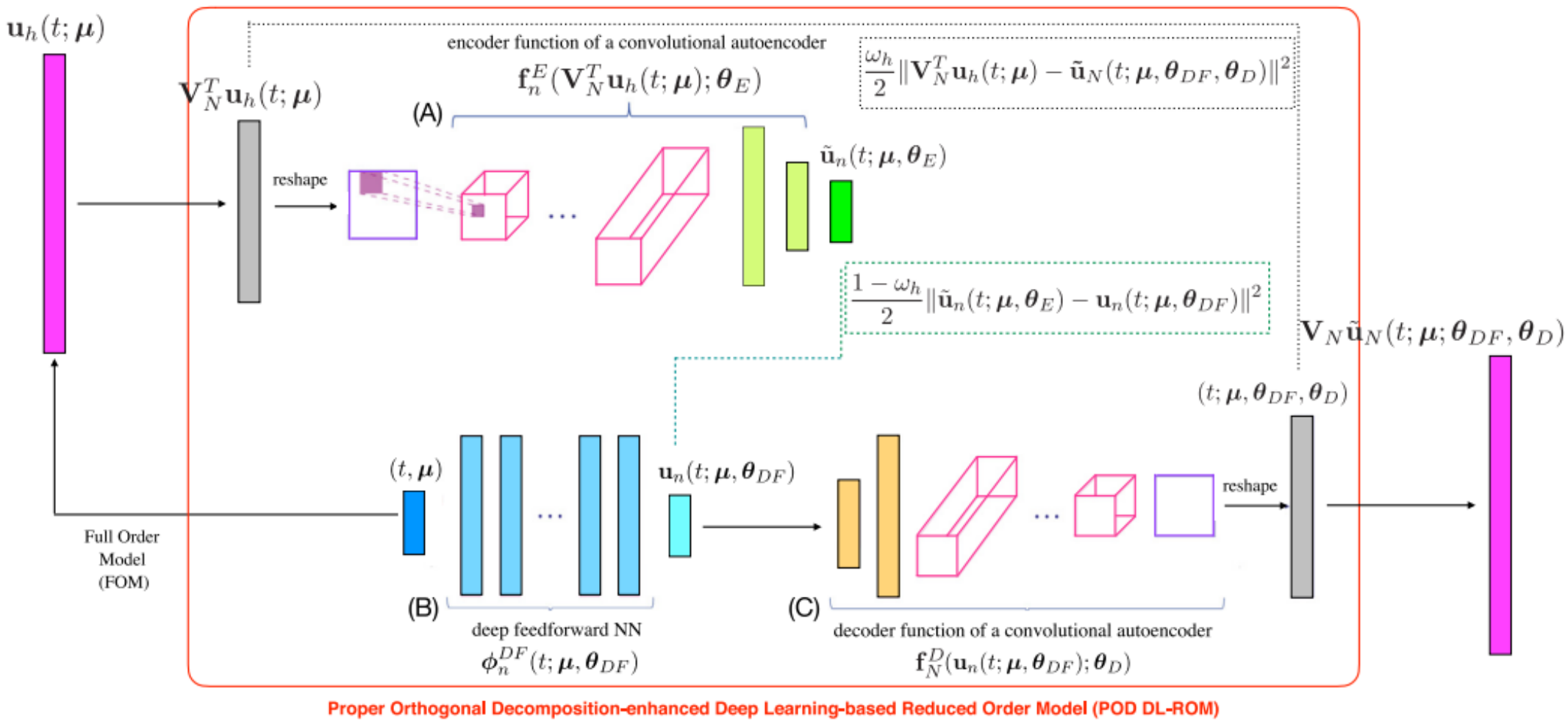


**Fig. 1.** POD-DL-ROM architecture. Starting from the FOM solution $\mathbf{u}_h(t;\boldsymbol{\mu})$, the intrinsic coordinates $\mathbf{V}_N^T\mathbf{u}_h(t;\boldsymbol{\mu})$ are computed, by means of rSVD, and the neural network provides as output $\tilde{\mathbf{u}}_N(t;\boldsymbol{\mu})$, an approximation of them. The reconstructed solution $\tilde{\mathbf{u}}_h(t;\boldsymbol{\mu})$ is then recovered through the rPOD basis matrix.

Stefania Fresca, Andrea Manzoni (2022) [2101.11845]