

# LONG-TIME PREDICTION OF NONLINEAR PARAMETRIZED DYNAMICAL SYSTEMS BY DEEP LEARNING-BASED REDUCED ORDER MODELS

Federico Fatone<sup>1</sup>, Stefania Fresca<sup>1</sup> and Andrea Manzoni<sup>1</sup>

<sup>1</sup> MOX - Mathematics Department, Politecnico di Milano,  
Piazza Leonardo da Vinci 32, I-20133 Milano, Italy,  
federico.fatone, stefania.fresca, andrea1.manzoni@polimi.it

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Deep learning-based reduced order models (DL-ROMs) have been recently proposed [1, 2] to overcome common limitations shared by conventional ROMs – built, e.g., exclusively through proper orthogonal decomposition (POD) – when applied to nonlinear time-dependent parametrized PDEs. POD-DL-ROMs, thanks to a prior dimensionality reduction through POD and a DL-based prediction framework, can achieve extreme efficiency in the training stage and faster than real-time performances at testing. Nonetheless, they share with conventional ROMs poor performances in time extrapolation tasks.

We thus aim at taking a further step towards the use of DL algorithms for the efficient numerical approximation of parametrized PDEs by introducing the  $\mu t$ -POD-LSTM-ROM framework. This novel technique extends the POD-DL-ROM framework by adding a two-fold architecture taking advantage of long short-term memory (LSTM) cells ultimately allowing long-term prediction of complex systems' evolution, with respect to the training window, for unseen input parameter values. Building predictions for future times based on the past, these coupled architectures mimic the behavior of common numerical solvers for dynamical systems.

This recurrent architecture enables the extrapolation for time windows up to 15 times larger than the training time domain and achieves better testing time performances with respect to the already lightning-fast POD-DL-ROM. In particular, we assess the performance of the proposed framework on several examples, obtaining faster than real-time simulations that are able to preserve a remarkable accuracy across the entire time domain considered during training.

## REFERENCES

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