# DEEP LEARNING-BASED KOOPMAN ANALYSIS FOR THE PREDICTION OF MULTI-BEAT CARDIOVASCULAR DYNAMICS

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## Introduction

The use of mathematical models in the cardiovascular domain is increasingly recognized for their potential in predicting diseases, planning therapies, and controlling medical devices. These models are usually composed of nonlinear ordinary differential equations (ODEs) that necessitate numerical solutions. However, this requirement often makes the solving process time-intensive, constraining their practical applications. For instance, employing these models within a model-predictive control algorithm for cardiac assistive devices demands predictions of multiple heartbeats within a second, a task challenging when using complex ODEs. Previously, we showed the potential of simplifying a lumped-parameter cardiovascular model using deep learning-based Koopman analysis for single heartbeats [1]. Here we present our preliminary findings on expanding the methodology to multiple heartbeats.

## Methods

The dataset was generated using a previously established lumped-parameter cardiovascular system model [2]. In total, 100 simulations of 10 s were performed for varying initial conditions, extracting 18 different hemodynamic signals of interest, including flows, pressures, and volumes in the heart and the circulatory system. All signals were sampled at 50 Hz and stored for further use. The data was z-normalized and split in ratio 8:1:1 into training, validation, and test sets, respectively. Each time series in the training set was split into sequences of 1 s with an overlap of 20 ms using a sliding window approach.

Following the work of Lusch et al. [3], a deep auto-encoder (4 layers, 30 hidden units) was used to transform the data into an intermediate space to linearize the system's dynamics. The transformed states were then fed into a second neural network (3 fully connected dense layers with 10 hidden units each). This network was employed to identify a finite set of Eigenvalues estimating the Koopman operator $K$. The obtained matrix $K$ is applied to predict future time steps of the hemodynamic states in the intermediate space. Finally, the results are transformed back into the original space using the decoder network.

To evaluate the network's prediction accuracy, the root mean squared error (RMSE) between prediction and ground truth was calculated for all normalized sequences in the test dataset. To assess the computational performance of the reduced model, the time required to predict 10 heartbeats was calculated.

## Results

Predicting 10 heartbeats (500 time steps) given only the initial condition resulted in an average z-normalized RMSE of 0.13 over the whole test set (Figure 1). For the predictions on an AMD Ryzen 7 PRO 4750U, the reduced model takes on average 0.78 s compared to 12.5 s using the full model. The variance of all obtained eigenvalues was below $1 \times 10^{-6}$, indicating the linearity of the reduced system.

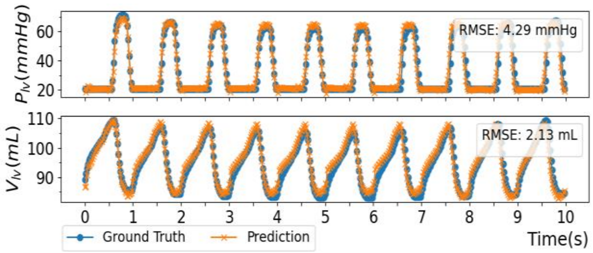


*Figure 1: Reduced model prediction versus ground truth of left ventricular pressure ($P_{lv}$) and volume ($V_{lv}$) for 10 s.*

## Discussion

The approach previously employed for a single heartbeat [1] was effectively applied for 10 heartbeats, highlighted by low RMSE and variance in Eigenvalues. The computational time of 0.78 s required for the prediction of 10 heartbeats represents a speed-up of factor 16 compared to the lumped-parameter model. Furthermore, it lies within a range suitable for use in model-predictive assays to control medical devices like neuroprostheses or circulatory assist devices.

Current work is directed towards the prediction of longer sequences with a particular emphasis on robustness against parameter changes, and optimization of network architecture to further enhance accuracy and computational performance.

## References

1. Haberbusch et al, ASAIO Journal, 69.2:113, 2023.
2. Haberbusch et al, Front Physiol, 11:579449, 2020.
3. Lusch et al, Nature Communications, 9:4950, 2018.

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