Physics Informed Neural Networks (PINN) for improving digital twins for a two-stroke engine

Degree programme: BSc in Mechanical Engineering
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This bachelor thesis investigates the use of Physics-Informed Neural Networks (PINNs) to improve digital twins for a two-stroke marine engine. The objective is to combine data-driven modeling approaches with physical knowledge in order to achieve both high computational speed and physical accuracy. The focus is on the development of continuous and discrete Physics-Informed Neural Network (PINN) models for dynamical systems.

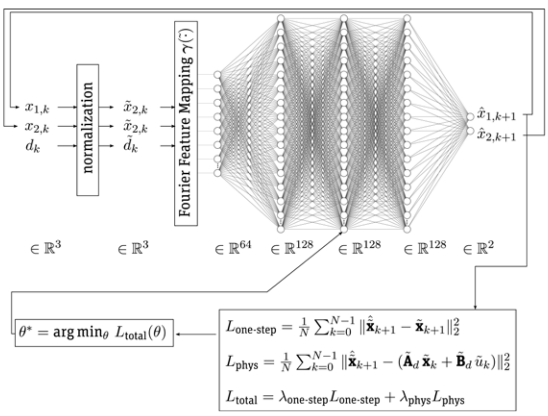
Initial situation

WinGD uses digital twins to optimize, simulate, and calibrate its marine engines. Classical data-driven neural networks offer high computational speed but lack physical accuracy. In contrast, simulation-based digital twins provide high physical accuracy but have limited computational efficiency. There is therefore a need for a hybrid approach that combines both high computational speed and high physical accuracy.

Objectives of the thesis

The objective of this thesis is to develop a Physics-Informed Neural Network (PINN) to improve the currently used simulation-based digital twin. The objectives are separated into three steps:

1. – Develop a foundational understanding of Physics-Informed Neural Networks (PINNs) by reconstructing existing methods for a continuous PINN applied to a homogeneous mass-spring–damper system.
2. – Develop a minimum viable product of a discrete PINN for an inhomogeneous mass-spring–damper system.
3. – Apply the discrete PINN to a WinGD-specific injection system.



Discrete PINN model architecture for an engine injection system

Methodology

First, a continuous Physics-Informed Neural Network (PINN) for a homogeneous mass-spring–damper system is implemented and validated. Furthermore, a discrete Physics-Informed Neural Network (PINN) including a normalization layer for an inhomogeneous mass-spring-damper system is implemented, which autoregressively predicts the next discrete system state vector from the previous state vector through a self-loop. The training process combines one-step, physics, and data losses to achieve physical accuracy. Code extensions include a curriculum learning strategy and a loss scheduler to improve performance. The discrete Physics-Informed Neural Network (PINN) is then applied to an engine injection system, where it is extended by a Fourier Feature Mapping Embedding. In this case, only the one-step and physics losses in the training process are used to achieve physical accuracy.

Results and future work

The continuous Physics-Informed Neural Network (PINN) demonstrates strong extrapolation and interpolation capabilities beyond the training data. The discrete PINN for an inhomogeneous mass-spring-damper system achieves a total loss of approximately 10^{-4} after 10 000 training epochs with a time step of 0.01 s, with the rollout loss contributing most to the total loss. Model validation through inference shows a mean squared error (MSE) of approximately 10^{-6} between the predicted and synthetic ground-truth position and velocity over a time span of 10 s. The discrete Physics-Informed Neural Network (PINN) for an engine injection system achieves a total loss of approximately 10^{-9} after 5 000 training epochs with a time step of 0.0001 s. A total mean squared error of approximately 10^{-19} between the predicted and synthetic ground-truth position and velocity is achieved in the model inference validation. Future work includes deploying the trained model on an industrial PC (IPC) and adapting it for real-time fault detection.

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