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Optimisation of CFD Simulations Using Multi-Fidelity Neural Networks

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[1]***Fidelity:*** *Fidelity defines the accuracy of a simulation when compared to the real world.*

1) INTRODUCTION

- Neural Networks (NNs) can be trained to learn physical problems encountered in CFD simulations to improve a simulation's run-time and accuracy.
- Although, to train an effective Neural Network, a costly dataset made of High-Fidelity[1] data must be used, negatively impacting time and cost efficiency of the training process.
- Multi-Fidelity Neural Networks (MFNNs) can overcome this limitation by combining multiple networks with varying fidelities forming a more precise and a faster model compared to a single Neural Network.

2) AIM & OBJECTIVES

Aim:

- Develop Multi-Fidelity Neural Networks to improve the precision, speed and scalability of CFD simulations to drive down costs in the engineering industry and academic research.

Objectives:

- Form and analyse the structure of Neural Networks using Python and PyTorch framework.
- Form Multi-Fidelity Neural Networks and evaluate their accuracy and efficiency compared to traditional Neural Networks.
- Optimize MFNNs to decrease the dependency of high-fidelity data in complicated CFD simulations.
- Implement Physics-Induced Neural Networks into the model to post-process CFD simulations more accurately.

3) METHODOLOGY

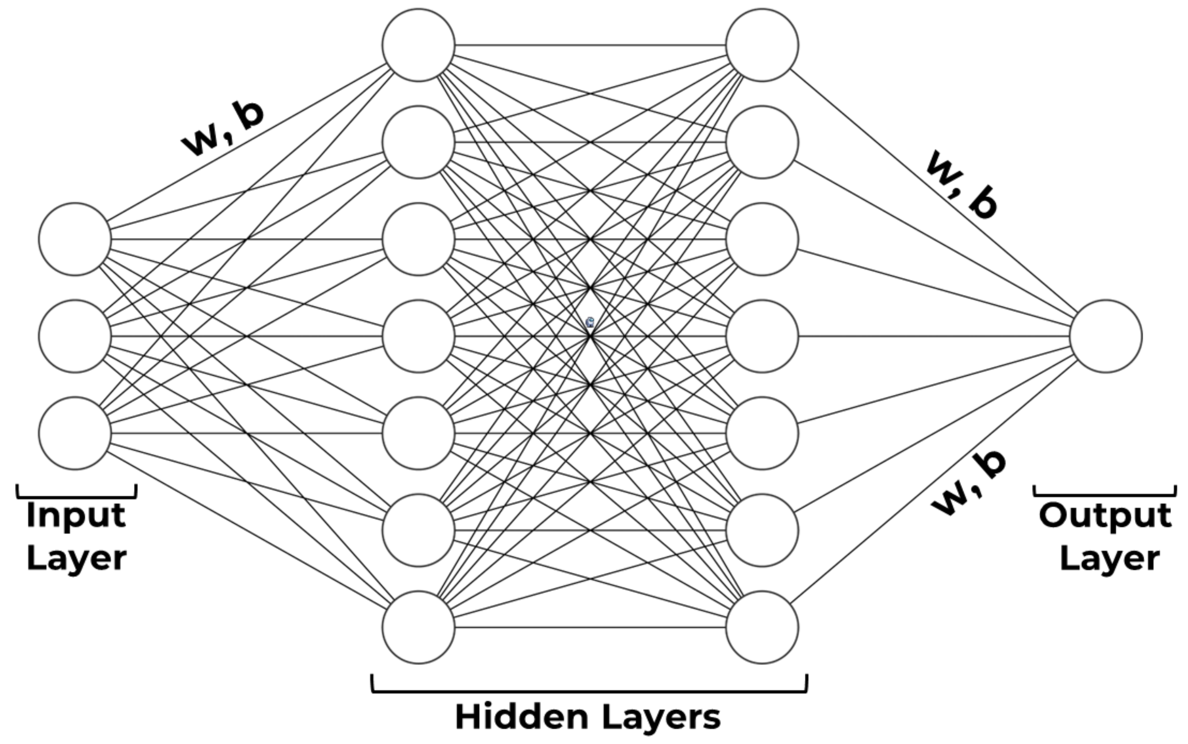

Figure 1: Simple Neural Network diagram

3A) Neural Networks

Neural Networks can serve as function approximators "[$\boldsymbol{y} \cong \boldsymbol{NN}(\boldsymbol{x})$]" which can learn the relation between given "$\boldsymbol{x}$" and "$\boldsymbol{y}$" values. They can be **trained** to predict results of CFD simulations since they can approximate "non-linear" and "multidimensional" functions, which are commonly encountered in CFD simulations.

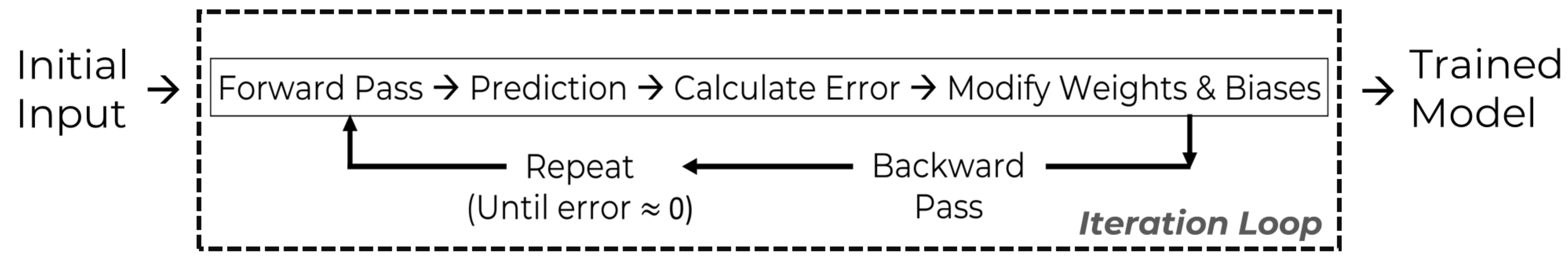

Figure 2: NN training process flowchart

Epochs = Number of Iterations

3B) Multi-Fidelity Neural Networks

Multi-Fidelity Neural Networks allow multiple NNs to be trained on different fidelities, capturing complex relations between the NN models forming a more accurate and an efficient model compared to a single Neural Network.

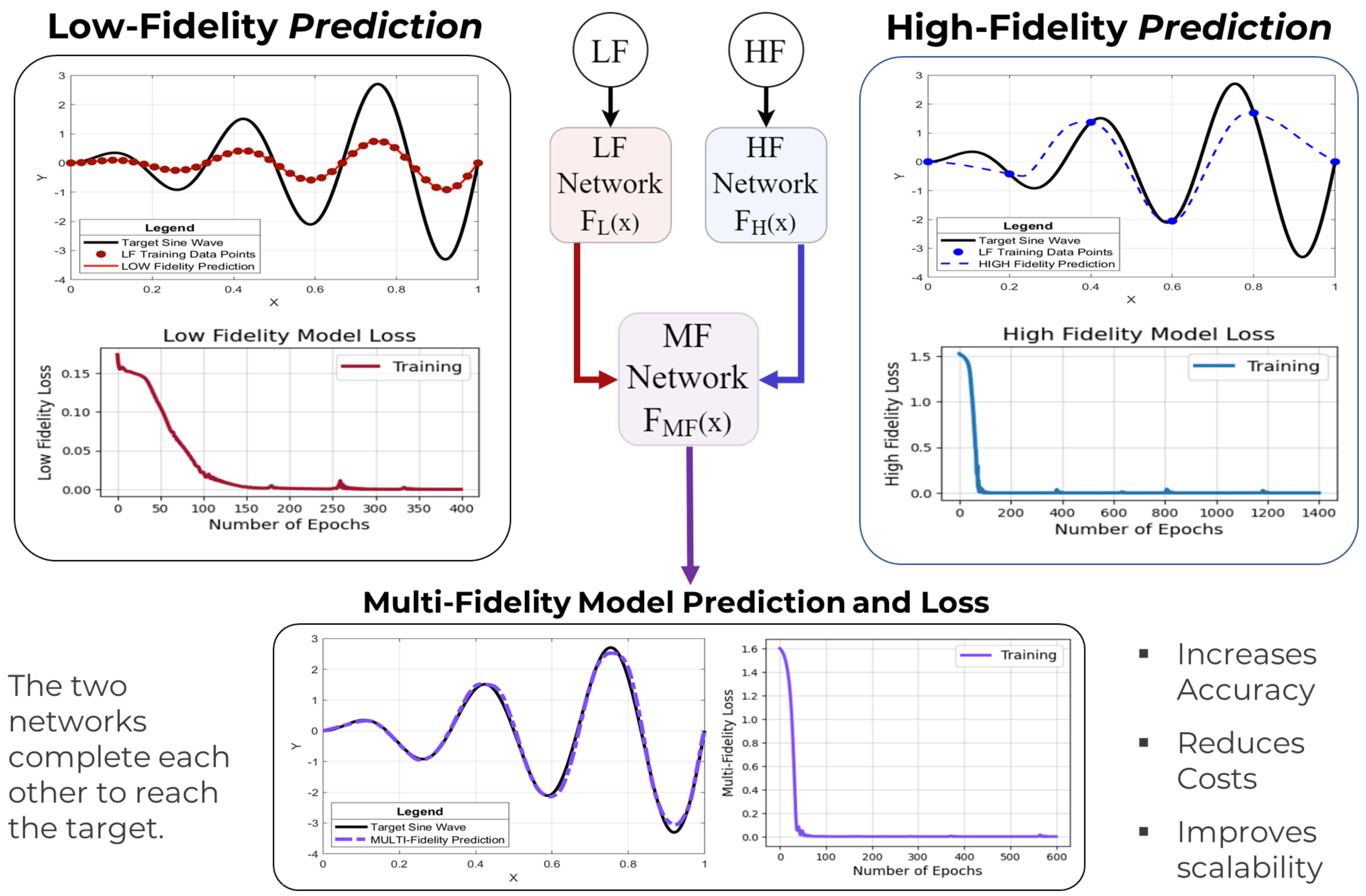

Figure 3: MFNN training process

4) PRELIMINARY RESULTS

MFNN has been trained with **two** NACA 4-digit aerofoils to represent two different dataset fidelities.

Figure 4 represents:

- The LF model was trained on NACA-2412 (red).
- The HF model was trained on NACA-0012 (blue).
- The MFNN model was trained on the LF and HF models.

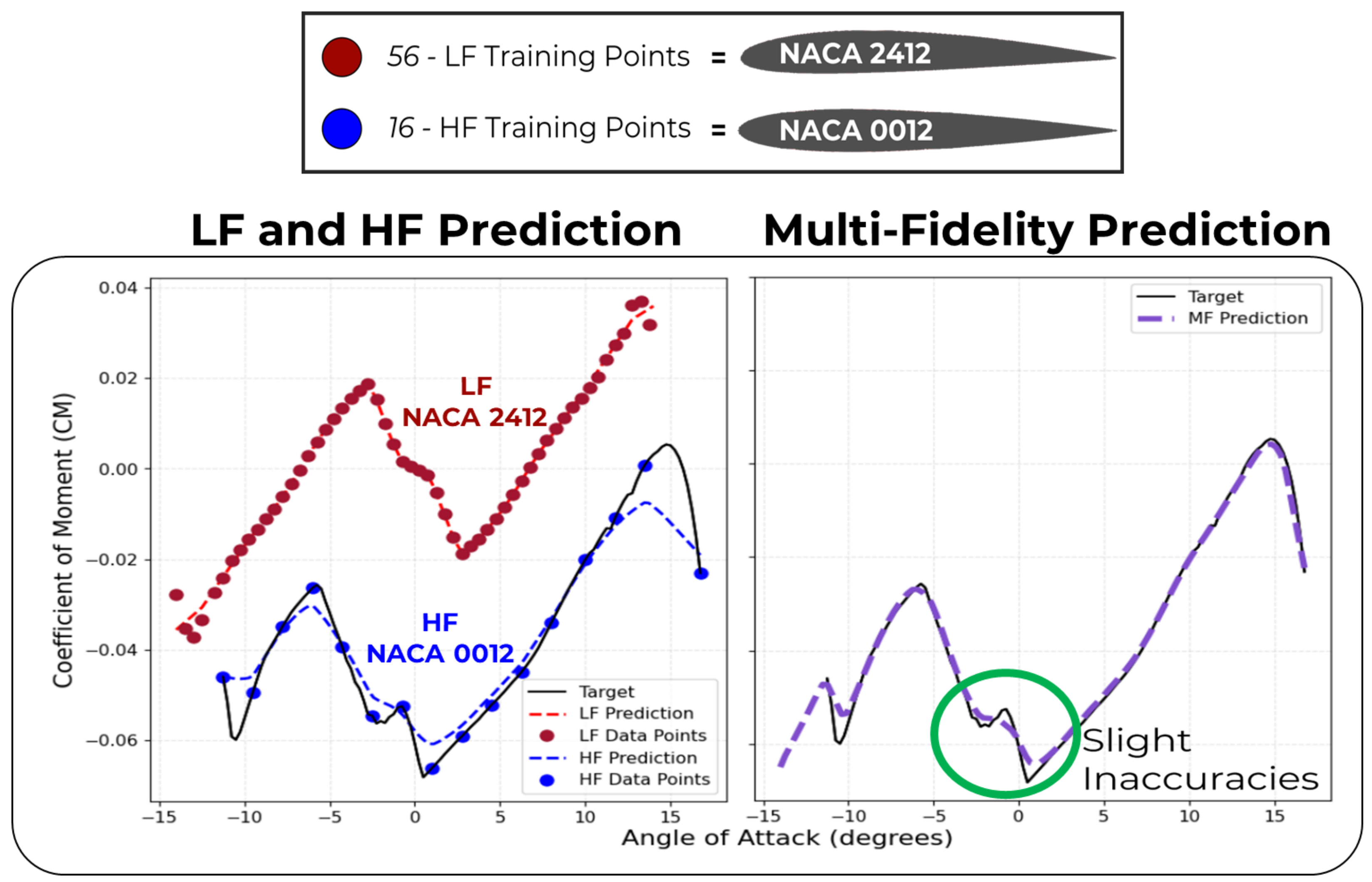

Figure 4: LF, HF and MF Predictions of Coefficient of Moment against Angle of Attack

Epochs	Error (in %)		
-	LF	HF	MF
100	67.0	75.1	45.5
200	29.4	52.6	33.2
400	22.6	44.9	19.3
800	12.8	31.7	7.2
Average	**32.9**	**54.1**	**26.3**

Table 1: Number of Epochs and Error of all models

Table 1 demonstrates the effect of number of epochs on model error.

When compared to the LF and HF models, the MFNN model significantly decreases the error of the final prediction.

5) FUTURE WORK

- Improve the model to run directly from raw data from a CFD simulation.
- Optimize the MFNN model to avoid failure when there is a phase shift between the datasets.
- Form Physics-Induced Neural Networks (PINNs) to incorporate physical laws and equations that govern the behavior of a simulation into the network's architecture.