Lucerne University of
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MSE | MASTER OF SCIENCE IN ENGINEERING

Master-Thesis Engineering, Specialization in Industrial Technologies

Improving Turbulence Models in RANS Simulations with Adjoint Method Field Inversion and Machine Learning Approaches

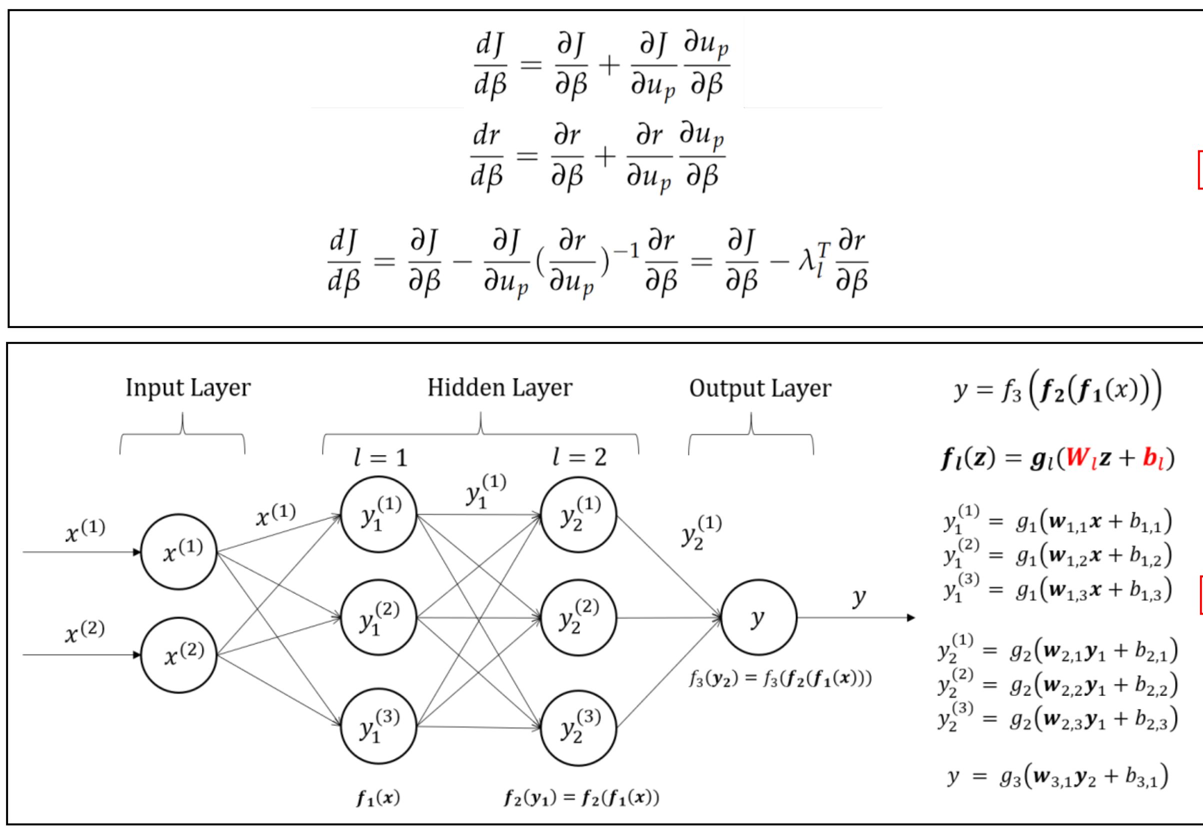

Figure 1: Building blocks of FIML: Adjoint driven optimization (top) and machine learning algorithms such as a neural network (bottom)

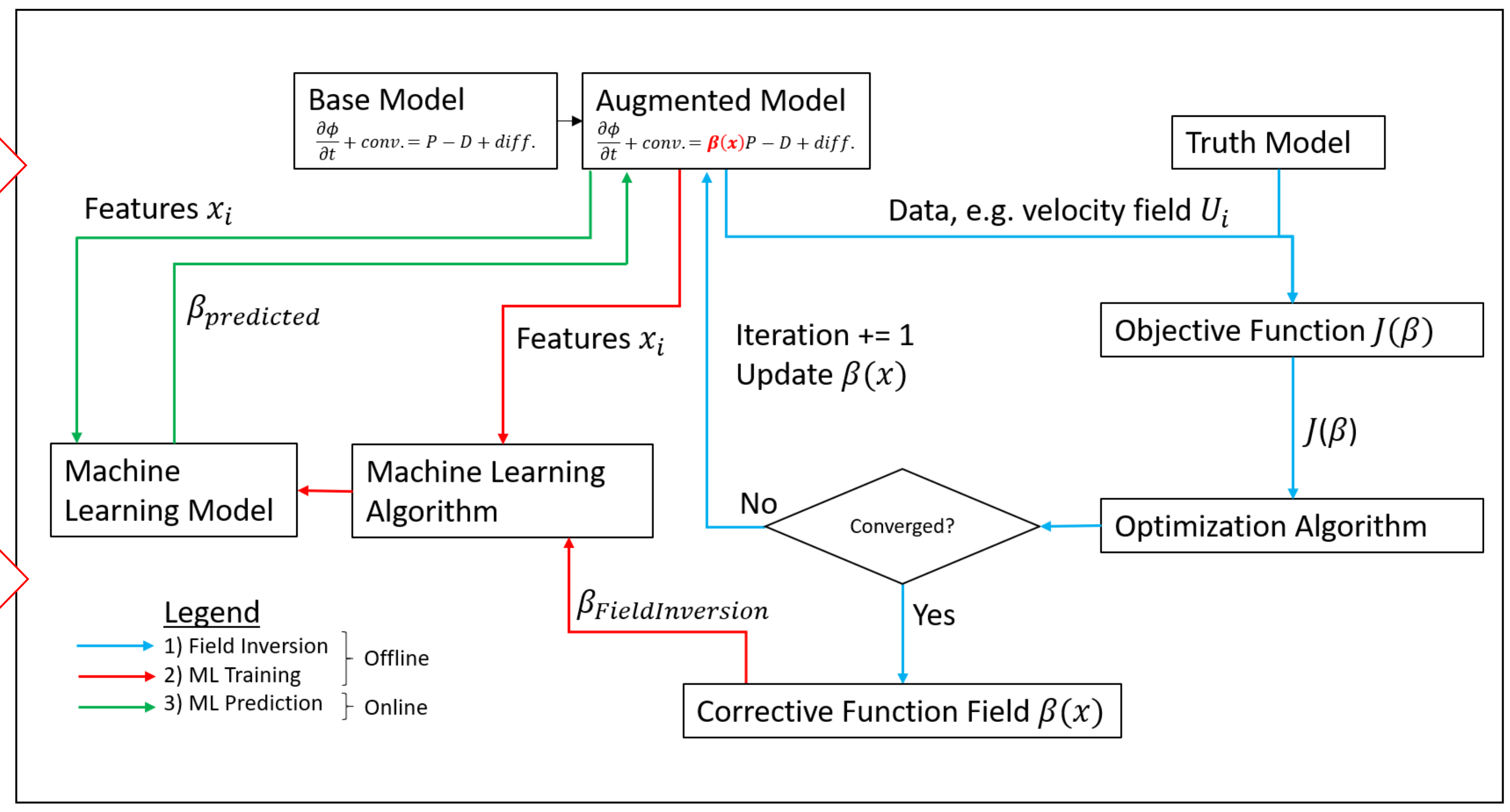

Figure 2: Overview of the Field Inversion and Machine Learning (FIML) paradigm

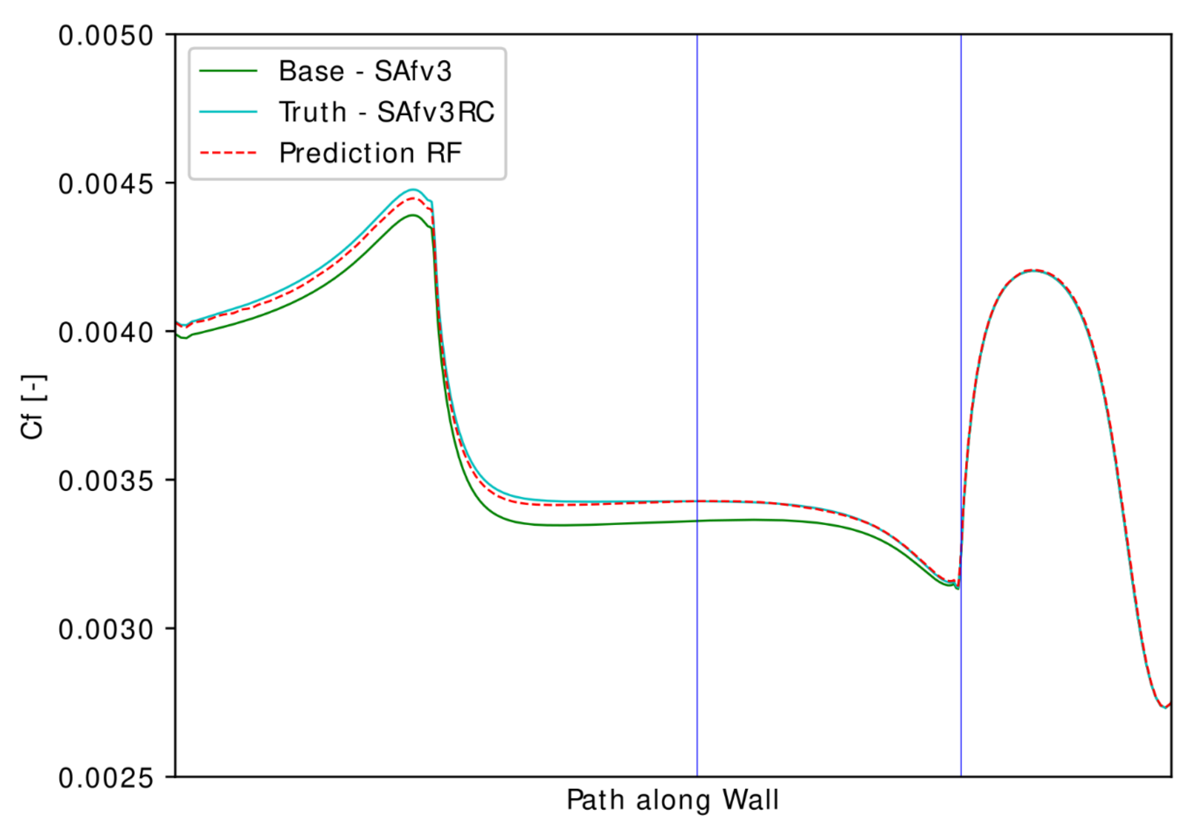

Figure 3: Prediction results of the friction coefficient (Cf) along the outer wall of a 90° pipe after training on varying geometries (U-turn, S-shape and >90° bend pipe)

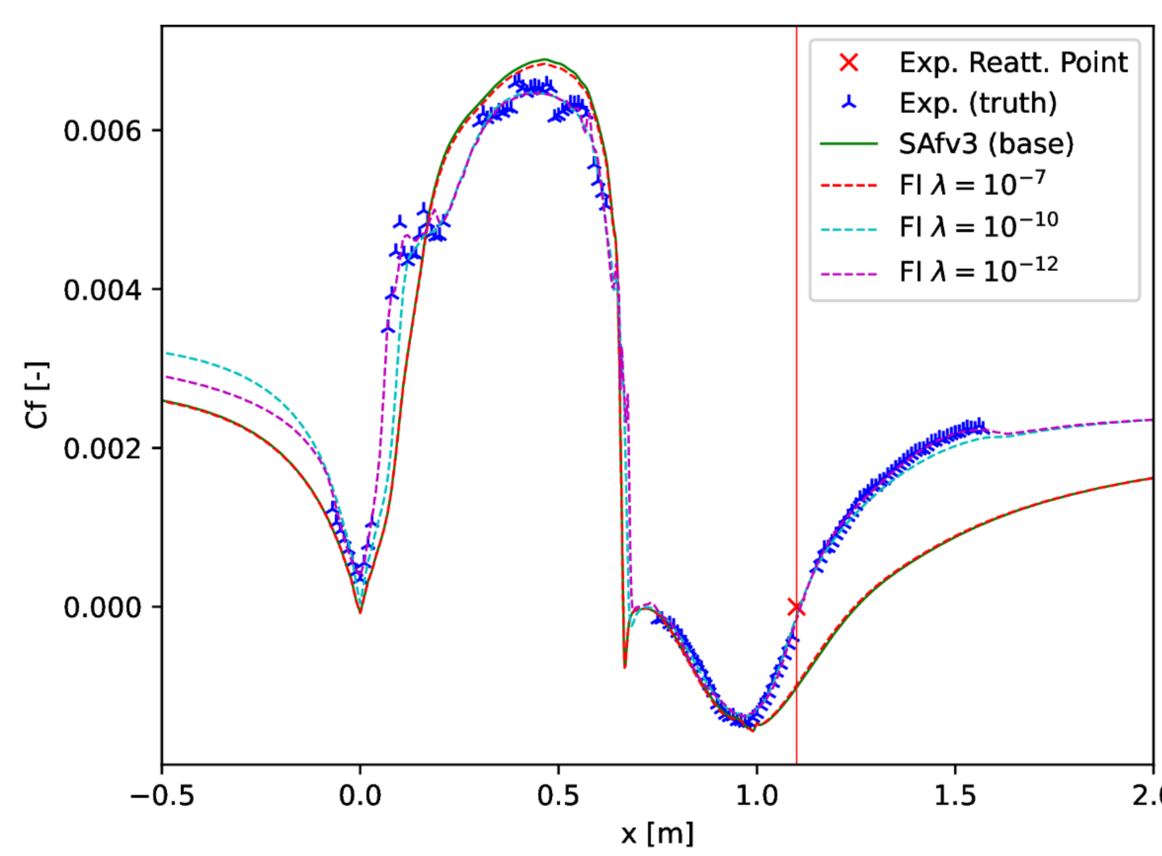

Figure 4: FI results using only sparse data (e.g. friction coefficient along boundary cell faces) for the formulation of the objective function on the hump geometry

Goal and Motivation

Data-driven modelling has gained momentum in science and engineering and Computational Fluid Dynamics (CFD) is an exemplary field to explore this approach. Central to this thesis is the specific framework of *Field Inversion and Machine Learning* (fig. 1, 2) [1, 2, 3, 4]. The goal is to apply the proposed framework within a given pressure-coupled CFD solver [5].

Methodology

In the Field Inversion (FI), an objective function is formulated in terms of the difference between the base model to be improved and the truth model (e.g. experimental data). Additionally, a Tikhonov regularization is applied. An optimization algorithm is employed to iteratively minimize this function and extract a discrepancy field. Secondly, a Machine Learning (ML) algorithm learns the relationship between this discrepancy field and selected features of the base model. The machine learning model is linked to the base model, capable of conducting simulations resembling the truth model.

Results

Using a U-turn pipe it is shown that the paradigm is capable of inferring the discrepancy field via an inverse problem using full-field data and that ML tools are able to recreate this field for new simulations. A random forest has been shown to be a better choice than a neural network. A generalization test proofs that the paradigm is capable of being applied to different flows and geometries, as long as they are similar (fig. 3). Using the friction coefficient as sparse data to inform the objective function for the hump, it is found that difficulties arise to obtain a result which neither under- nor overfits the truth model data during the FI (fig. 4).

Discussion

The results of this thesis have shown that the Field Inversion and Machine Learning framework poses vast potential in improving RANS turbulence models. Further testing is needed, especially using sparse data as truth model to investigate the overfitting during the FI. A Bayesian formulation of the objective function might leverage the optimization. Feature and algorithm selection for the ML should be further investigated to find a more general model capable of predicting a variety of flows and geometry settings.

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References

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[3] K. Duraisamy and S. Shaowu. "Augmentation of Turbulence Models Using Field Inversion and Machine Learning". In: *55th AIAA Aerospace Sciences Meeting* (2017)

[4] A. P. Singh, S. Medida, and K. Duraisamy. "Machine-learning-augmented predictive modeling of turbulent separated flows over airfoils". In: *AIAA Journal* (2017)

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